APPLYING NEURAL NETWORKS FOR TIRE PRESSURE MONITORING
SYSTEMS

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Alex Kost

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COMMITTEE MEMBERSHIP

TITLE: Applying Neural Networks for Tire Pressure Monitoring Systems

AUTHOR: Alex Kost

DATE SUBMITTED: March 2018

COMMITTEE CHAIR: Mohammad Noori, Ph.D.
Professor of Mechanical Engineering

COMMITTEE MEMBER: Xiao-Hua Yu, Ph.D.
Professor of Electrical Engineering

COMMITTEE MEMBER: Franz Kurfess, Ph.D.
Professor of Computer Science

COMMITTEE MEMBER: William Murray, Ph.D.
Professor of Mechanical Engineering

ABSTRACT

Applying Neural Networks for Tire Pressure Monitoring Systems

Alex Kost

A proof-of-concept indirect tire-pressure monitoring system is developed using neural networks to identify the tire pressure of a vehicle tire. A quarter-car model was developed with Matlab and Simulink to generate simulated accelerometer output data. Simulation data are used to train and evaluate a recurrent neural network with long short-term memory blocks (RNN-LSTM) and a convolutional neural network (CNN) developed in Python with Tensorflow. Bayesian Optimization via SigOpt was used to optimize training and model parameters. The predictive accuracy and training speed of the two models with various parameters are compared. Finally, future work and improvements are discussed.

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Chapter 1

INTRODUCTION

1.1 Background

It is difficult to understate how important properly pressurized tires are to the performance and safety of a vehicle and its operator, respectively. The National Highway Traffic Safety Administration (NHTSA) estimates that 11,000 tire-related crashes occur annually in the US, with 200 people estimated to be killed in these crashes [28]. Furthermore, under-inflated tires contribute to the following performance issues when driving [37]:

1. Poor fuel economy, wasting an estimated 3.5 million gallons daily and costing drivers as much as 11 cents per gallon in the US.
2. Longer stopping distances and sluggish/ineffective handling, resulting in more dangerous driving conditions.
3. Faster tire wear, reducing the average life of a tire by 4,700 miles.

Tire-pressure monitoring systems (TPMS) became federally mandated in 2000 by the Transportation Recall Enhancement, Accountability, and Documentation Act, where legislators ruled to “require a warning system in new motor vehicles to indicate to the operator when a tire is significantly under inflated” [38]. More specifically, all motor vehicles must have a system that is capable of detecting when one or more of the vehicle’s tires, up to all four tires, is 25% or more below the manufacturer’s recommended inflation pressure or a minimum activation pressure specified in the standard, whichever is higher [25]. Nonetheless, a study performed in April 2009 showed that 45% of TPMS-enabled vehicles still have under-inflated tires [26].

Therefore, for obvious moral and legal reasons, it is imperative that drivers know that their tires are inflated properly. It is in the individual’s and society’s best interests

to improve safety, performance, and savings while on the road.

1.2 Purpose

The most commonly used TPMS in vehicles today is a simple pressure sensor mounted within the tire to directly measure the pressure of the air within the tire. When the integrated battery dies on these sensors, the sensors must be replaced manually. Time, money, and labor are spent to replace this simple sensor. It would be advantageous if the TPMS architecture was created such that maintenance and repair were not needed.

As advancements in machine learning and deep learning techniques continue, it is no longer a question of *how* or *why* to apply these techniques, but *where* to apply them. In this work, a proof-of-concept TPMS architecture is suggested that uses accelerometer data and deep learning algorithms to determine whether the tires on a vehicle are under, over, or nominally inflated. This work comprises four chapters:

1. **Chapter 1** introduces the legal and moral motivations behind TPMSs in today's vehicles. This chapter also outlines the content of this work.
2. **Chapter 2** serves as a literature review for this work. Three specific fields of study are defined: a mechanical review of automotive suspension systems and tires, current TPMS frameworks and sensing capability, and current technologies and research in artificial neural networks.
3. **Chapter 3** presents the work done to create a proof-of-concept classifier using simulated data. The simulated model and its limitations are discussed, as well as the architecture and modifications done on the artificial neural network.
4. **Chapter 4** compares the final performance of the implemented classifiers and concludes this work with a discussion on the meaning and limitations of the results. Suggestions for future work are also made.

Chapter 2

THEORY

2.1 Suspension and Tires

Vehicle suspensions and tires are designed to optimize the traction, ride comfort, handling, and fuel consumption of the vehicle. The suspension links the *wheels*—tires mated to rims—to the vehicle chassis and allows relative motion, while the tire transfers energy between the vehicle and the road to allow the vehicle to move [16]. Together, the suspension and tires are the defining aspects of a vehicle’s combined stiffness and damping coefficients.

A simplified representation of a vehicle suspension system is used in this work. Known as a *Quarter Car Model*, the representation has only one degree-of-freedom and can only move vertically. The vehicle is rigid; only vibrations transferred from the ground to the tires, axles, and suspension systems are considered. This representation also does not consider any forces or reactions due to the geometry of the vehicle; it is only looking at a single wheel on this “vehicle.” The representation is presented in Figure 2.1 [16].

The unsprung mass m_u refers to all masses that are attached to and not supported by the spring, such as the wheels, axles, or brakes. In this representation, the unsprung mass is the weight of the tire and the weight of the air of the tire. In an actual vehicle, suspension stiffness and damping values k_s and c_s are functions of suspension type, tire geometry, tire pressure, vehicle geometry, and vehicle weight. These values should be constant in vehicles without active suspension systems, so the only changing parameter in this model is the unsprung mass’s stiffness k_u . Any damping in parallel with k_u is negligible with respect to c_u and is thus not included in the representation.

Figure 2.1: A free-body diagram of the quarter-car model. Taken from *Jazar et al.* [16].

2.2 TPMS Architectures

The NHTSA provides vehicle manufacturers three ways to comply with the law: direct, indirect, and hybrid TPMS [27]. Direct TPMS consists normally of pressure sensors located inside each wheel to directly measure the pressure in each tire. Indirect TPMS compares speed data collected from vehicle's anti-lock braking system wheel speed sensors to compare rotational speeds of tires against one another to determine the pressure. Direct systems are more accurate and precise, whereas indirect systems are less hardware-dependent and more robust for each vehicle. The NHTSA leaves the definition of a hybrid TPMS purposefully vague and suggests such a system would use a combination of direct and indirect methods to fulfill the regulatory requirements. Although direct TPMS dominates the method today, indirect TPMS is expected to become the dominant TPMS in the coming years.

A note should be made that not all direct and indirect TPMS are created equal: individual features differ from system to system. As shown in *Kubba and Jiang* [21], various direct TPMS systems use different power sources and sensing solutions.

Research of indirect TPMS frameworks has grown and continues to grow because of their perceived advantages over direct TPMS as computing power increases. For

example, *Persson, Gustafsson, and Drev* [31] presented in 2002 an indirect TPMS combining vibration and wheel radius analyses was able to detect pressure losses larger than 15% in one, two, three, or four tires and identify the underinflated tire within 1 minute.

2.3 Artificial Neural Networks

An *artificial neural network* (ANN) is a machine learning algorithm used to solve advanced non-linear problems such as handwriting or speech recognition. Neural networks connect computational nodes together to form a singular “network,” where each computational node is performing a calculation on its input and outputting the result to all outgoing connections. The output of a node can be the input to at least one other node or to many other nodes. Outputs can be scaled and biased by *weights* and *biases* respectively; think the canonical linear function $y = mx + b$, where y is the original output, m is the weight, x is the new output, and b is the bias. Often, *activation functions* are added to the networks; these further define the output with a linear or non-linear function. As shown by *Ramachandran et. al* [34], the most commonly used activation function in deep learning projects is the *rectified linear unit* (ReLU). In summary, interconnected computational nodes perform linear and non-linear operations on inputs.

At first, all ANN models do not perform well because the weights and biases are not tuned; that is, the model is not *trained*. Neural networks can learn a hierarchical feature representation from raw data automatically [40]; that is, they “learn” or can be trained through example. In this work, we train our models via *supervised learning*—that is, with labeled training data—and compare the model’s predictions to the actual labels. By repeatedly minimizing the error between prediction and truth, the model updates the trainable parameters and its accuracy improves. This updating is based on minimizing a *cost* (generally inversely proportional to accuracy) via some optimization strategy. *Gradient Descent* strategies are often implemented; in this work, the *Adaptive Moment Estimation* (Adam) strategy is applied. Adam computes adaptive learning rates for each parameter and takes advantage of the

idea of *momentum* to more quickly converge on the global minima with reduced oscillation [20].

Furthermore, models hyperparameters can be *tuned* such that they can more quickly be trained and perform more optimally. *Grid search* tuning is a standard method where an exponentially large grid of possible hyperparameter combinations is systematically searched. Alternatively, *Bayesian Optimization* tuning promises a more intelligently search by learning from prior hyperparameter combinations and their results to intelligently suggest better combinations [6]. Grid searches are exponentially expensive whereas Bayesian optimization are only linearly expensive, as visualized in Figure 2.2. In this work, the software-as-a-service product *SigOpt* is applied to perform Bayesian optimization techniques for quick, intelligent tuning.

Figure 2.2: (a) Grid Search vs. (b) Bayesian Optimization techniques for tuning, where each yellow dot indicates a model evaluation. Notice that grid searches could be searching along a potentially-coarse grid, whereas Bayesian optimization techniques test any possible combination within the space and intelligently suggests combinations to reach optimal solutions with fewer evaluations.

The type of input data generally defines the type of ANN to be used; in this case, the models are interpreting time series data. As defined by *Dorffner* [8], a *time series* is a sequence of vectors depending on time t such that $\vec{x}(t), t = 0, 1, 2$, and so on. The components of $\vec{x}$ at each time t (referred to as *datapoints* in this work) are distinct from one another but are not informative enough to extrapolate meaningful

information from the time series; instead, each datapoint in a time series must be analyzed in relation to the rest of the time series. We discuss two major model types for interpreting time series data below: the *recurrent neural network* (RNN) and *convolutional neural network* (CNN).

Figure 2.3: A visual representation of a single block in a recurrent neural network (RNN). Taken from [29].

Recurrent neural networks (RNNs) interpret time-series data successfully by adding feedback loops to the standard ANN network architecture [22] [9]. Some RNNs use more complex computational nodes known as *long short-term memory* (LSTM) blocks to mitigate an issue common in RNNs known as the *vanishing gradient problem* [9].

Figure 2.4: Visualization of a 5x5 filter convolving around an input volume and producing an output. Taken from [5].

Convolutional neural networks (CNNs) interpret clusters of datapoints (e.g. time-series, images, sentences, sound recordings, so on) together to preserve spatial or temporal relationships. CNNs apply *kernels* or *filters*—i.e. a weight matrices—to recognize and extract features or patterns [19].

The first few layers of a typical ANN act as *feature extractors*; that is, they are responsible for extracting meaningful information from the input data. For example,

RNNs build an internal memory and CNNs use pattern matching. This meaningful information is then fed into a *classifier*. Classifiers are generally *fully-connected layers* (each node is connected to one another; see Figure 2.5) with n outputs, where n is the number of classes in the input data.

Figure 2.5: Visualization of a fully-connected layer. Taken from *Holle-mans et al.* [13].

ANNs have been applied in the automotive industry for decades. In 1990, *Wiggins* presented a neural network that could identify engine faults based on the vehicle’s engine controller data [39]. Neural networks were used to control the air-to-fuel ratio in fuel injection systems as shown by *Alippi et al.* in 2003 [2]. More recently, ANNs have driven advances in automated vehicle control (“self-driving”) that can detect, identify, and respond to objects and pedestrians on the road in real time. While Tesla, Mercedes-Benz, and BMW were first introduce these features to consumer vehicles, the technology is becoming increasingly ubiquitous [17]. A NHTSA investigation conducted in January 2017 found crash rates Tesla crash rates have dropped by almost 40% since enabling self-driving capabilities in 2015 [12].

Applying ANNs to automobiles requires dedicated software and hardware on the vehicle. Unlike data centers, portable implementations are limited primarily by the size, energy, and computational power of the device they are operating on [33]. Size is generally not a constraint for automotive manufacturers. Energy and computational power are proportional: therefore, research has been focused on improving microprocessing architectures to minimize energy draw (hardware) or improving the efficiency

of the algorithm to reduce computational load (software). With respect to hardware, in February 2016, researchers presented a convolutional neural network accelerator chip that uses 10X less power and requires 4.7x fewer DRAM accesses per pixel than a mobile GPU [4]. Similarly, with respect to software, AlphaGo, a Google project, demonstrated that integrating classification trees with neural networks significantly reduces the computational burden, making what people once thought impossible—a computer defeating a world-champion Go player in real time—possible [35]. Many more examples like these can be found.

Chapter 3

WORK

With the desire to explore alternative indirect TPMS frameworks and inspired by deep learning is seemingly infinite applications, this work explores a deep learning framework that analyzes vehicle suspension acceleration data to classify the vehicle tires as under-inflated, nominally inflated, or over-inflated. To validate this idea, work was broken into the following sections:

1. **Collecting Data.** The accuracy and capability of the ANN is largely dependent on the size of our data—ANNs tend to improve when there is more data for training. In this work, data was simulated by a quarter-car model written in Matlab and Simulink. The data serves as the training, validation, and test sets for the ANN.
2. **Creating the Algorithm.** Using the data from the prior step, an RNN-LSTM and CNN are developed in Python with Google’s open-source TensorFlow API. Tuning model and training parameters are done using Bayesian Optimization via SigOpt.

3.1 Collecting Data

A Matlab model for the quarter-car representation as shown in Figure 2.1 was run at various tire pressures and step-sizes to generate simulated examples of a vehicle suspension system experiencing a step response (in an attempt to be analogous to a pothole or speed bump). The simulation solves the system of ordinary differential equations for every time step for the position, velocity, and accelerations of the sprung mass m_s and unsprung mass m_u . The simulation inputs are presented below in Table 3.1 and their accompanying derivations are presented in Appendix A.

Table 3.2: Inflation classifications, pressures, and labels.

Inflation Classification	Pressure Range (psi)	Label (int)
Under	26–30	0
Nominal	30–34	1
Over	34–38	2

Table 3.1: Simulation input variables.

Variable	Description	Value	[Units]
p_u	Tire pressure	Varies	[psi]
y	Step size	Varies	[m]
m_s	Sprung mass	277.25	[kg]
m_u	Unsprung mass	34.69	[kg]
k_s	Sprung stiffness	557.97	[kPa]
c_s	Sprung damping	6218.35	[Pa-sec]
k_u	Unsprung stiffness	Varies	[kPa]
g	Gravity	9.81	[m/sec ²]

The simulation was performed for $p_u = 25.5, 26, 26.5, 27, \dots, 38.5$ and for $y = 0.10, 0.15, 0.2, \dots, 2.0$, generating 633 total examples. Every 1.5-second-long run is composed of 1500 data points and labeled according to the inflation classifications as defined by Table 3.2. These classifications are 10% of 32 psi, well within the 25% specification as defined by the TREAD Act. The label of the simulation and the sprung’s mass acceleration $\ddot{x}_s$ are saved in individual .csv files to be parsed by the algorithm. An example of the generated data is presented below in Table 3.3 (note that the first row is only shown here for clarification and is not included in the raw output).

Table 3.3: Example of simulated data: Sim_35.5psi_0.75m.csv.

label	$\ddot{x}_s, t = 0.000s$	$\ddot{x}_s, t = 0.001s$	...	$\ddot{x}_s, t = 0.420s$	$\ddot{x}_s, t = 0.421s$
2	-0.00073852	-0.00067152	...	-1.3974	-1.2822

Plots were developed of x_s vs. time as a quick sanity check. The plots make intuitive sense—higher pressure correlates with greater stiffness, which then increases the natural frequency, slows the settling speed of the mass, and reduces the maximum amplitude. The simulation is sound.

Figure 3.1: Sprung mass vs. time for $p_u = 26, 32, 38$ psi for step size $y = 2$ m.

3.2 Building the Algorithm

3.2.1 Specifications

For this work, TensorFlow was used to build, train, and evaluate a RNN and a CNN. Development of each neural network followed the same specifications as listed below.

1. Import the simulated data into the Python environment.
 - (a) The input data shall be shuffled randomly.
 - (b) The input data shall be split into a training set (60%), validation set (20%), and test set (20%).

2. Build the model of the neural network.
 - (a) The model shall be fed labeled input data and output predicted labels.
 - (b) The input data should be fed in batches to minimize computational load between parameter updates. Generally, the recommended starting batch size is 32 [3]
 - (c) The model shall prevent overfitting by applying dropout to the outputs of at least one fully-connected layer [32].
 - (d) *Batch normalization* shall be applied after various layers to reduce the internal covariate shift within the model [15].
 - (e) Model logits shall be converted to classification predictions using the softmax activation function.
3. Evaluate the predictive capabilities and training speed of the model.
 - (a) The cost shall be calculated using the cross-entropy function between the input data labels and model predictions [24].
 - (b) The accuracy shall be calculated by comparing the model's predicted labels to the input data labels.
 - (c) The training speed shall be minimized by tuning the model hyperparameters.
4. Train the model parameters.
 - (a) The training shall end after a predefined number of epochs and not be stopped early to observe any overfitting in the model.
 - (b) The training method shall minimize the batch's average cross-entropy loss using *Adam Optimization* strategy [20].
 - (c) The learning rate shall be static or exponentially decaying.

3.2.2 Development

The RNN-LSTM and CNN models are self-contained in `RNNModel` and `CNNModel` respectively. Both models are similar except for the feature extraction near the input

layer of the model.

Figure 3.2: (a) RNN-LSTM and (b) CNN model visual graphs as created by TensorBoard.

A `DataProcessor` class was written to provide methods to scan a directory for all files and perform various preprocessing operations. In this work, `DataProcessor` scans the simulated data directory; generates lists of all files found across all labels; shuffles and splits the filenames across test, validation, and training sets; and loads the feature data and label data found in each files from each set into member variables to be used for training.

The training class `TrainModel` is the entry point to train the model. Instantiating `TrainModel` builds the desired model with a provided learning rate `learning_rate` and dropout rate `dropout_rate`. Calling `train_model` trains the model for a desired number of epochs `n_epochs` using feature and label data inherited from `DataProcessor`. Every $\frac{1}{n_checks}$, the model's accuracy and cost are evaluated across the entire training and validation datasets and reported to TensorBoard for visualization. The test set accuracy is evaluated before and after training.

3.2.3 Tuning

The model parameters were tuned via SigOpt to identify optimal values for various model hyperparameters. Tuning classes `GridSearchTune` and `SigOptTune` were developed to perform a grid search or connect to SigOpt to perform a Bayesian search respectively. It was estimated that a grid search over the entire model space would take over two weeks of computations per model, whereas SigOpt’s more-intelligent Bayesian search strategy would take days instead. Thus, only `SigOptTune` was used in this work.

Two SigOpt experiments were run for each model to optimize the training speed and accuracy respectively. The parameters under investigation are listed below in Table 3.4.

Table 3.4: Parameters optimized via SigOpt Bayesian optimization. * denotes that the parameter is related to Adam optimization strategy

Name	Description	RNN-LSTM	CNN
<code>dropout_rate</code>	Dropout rate	X	X
<code>learning_rate</code> *	Learning rate	X	X
<code>beta1</code> *	1st moment estimates exponential decay rate	X	X
<code>beta2</code> *	2nd moment estimates exponential decay rate	X	X
<code>epsilon</code> *	Numerical stability constant	X	X
<code>num_filt_1</code>	Number of filters in convolutional layer		X
<code>kernel_size</code>	Kernel size in convolutional layer		X
<code>num_fc_1</code>	Number of neurons in first fully-connected layer	X	X
<code>n_layers</code>	Number of hidden layers in model	X	
<code>n_hidden</code>	Number of features per hidden layer in LSTM	X	

All source code is available in Appendix B.

Chapter 4

RESULTS AND CONCLUSIONS

4.1 Initial Results

Tuning the Adam-specific hyperparameters gave insight in a recurring issue with the LSTM-RNN: The model would not improve in performance after 200 steps (40 epochs with `batch_size = 128`). Figure 4.1 shows multiple training curves with various values for `learning_rate`, `beta_1`, `beta_2`, and `epsilon`. where the cross-validation accuracy would remain at 33.3%, or the same accuracy as randomly guessing.

Figure 4.1: RNN-LSTM: Training classification accuracy for various Adam optimization strategy optimization parameters `learning_rate`, `beta_1`, `beta_2`, and `epsilon`.

These results can be from the RNN-LSTM’s inability to identify any meaningful features after 40 epochs of the 633 training examples. The same results were seen when the model was trained for 200 epochs: The RNN-LSTM underfit the simulated data every time. Therefore, all model hyperparameters were increased. The resulting models successfully fit the input data and achieved significantly better accuracy when classifying the test set data. Further hyperparameter tuning showed that increasing the number of layers to be greater than 1 results in the model fitting the data appropriately. After 100 observations, Sigopt reported the RNN achieved 96.2% accuracy.

The CNN did not require much hyperparameter tuning. The CNN achieved near state-of-the-art success (accuracy > 95%) on the first try. The CNN achieved 100% accuracy after 15 optimization evaluations with SigOpt.

The final model hyperparameters were based on the first evaluation that classified the test set with 100% accuracy. These values are shown in Table 4.1. Similarly, the final performances are shown below in Figure 4.2.

Table 4.1: Final hyperparameters chosen for both models.

Name	RNN-LSTM	CNN
dropout_rate	0.672	0.309
learning_rate	0.00001	0.033
beta1	0.9	0.684
beta2	0.999	0.845
epsilon	1e-08	0.282
num_filt_1	-	16
kernel_size	-	4
num_fc_1	31	6
n_layers	4	-
n_hidden	22	-

4.2 Final Results and Discussion

Overall, both CNN and RNN models achieved above 90% accuracy on the validation and test dataset given sufficient time. Figure 4.2 depicts the accuracy curves during training across the training and validation datasets.

Different training parameters and hyperparameters were defined for each model to achieve these results. The training parameters of both models saw a change in the batch size `batch_size` and number of epochs `n_epochs`. The batch size was increased from 32 to 256 so each model update would better represent the dataset. The models

Figure 4.2: Classification Accuracy During Training

were ran until a validation dataset accuracy above 90% was observed, hence the final value `n_epochs` = 1000.

The CNN requires significantly less time to train than the RNN-LSTM. This can be explained by looking at the mathematics behind the architectures. At each time step t , a RNN-LSTM must perform the following computations:

$$\begin{aligned}
 \mathbf{g}^u &= \sigma(\mathbf{W}^u \mathbf{h}_{t-1} + \mathbf{I}^u \mathbf{x}_t + \mathbf{b}_u) \\
 \mathbf{g}^f &= \sigma(\mathbf{W}^f \mathbf{h}_{t-1} + \mathbf{I}^f \mathbf{x}_t + \mathbf{b}_f) \\
 \mathbf{g}^o &= \sigma(\mathbf{W}^o \mathbf{h}_{t-1} + \mathbf{I}^o \mathbf{x}_t + \mathbf{b}_o) \\
 \mathbf{g}^c &= \tanh(\mathbf{W}^c \mathbf{h}_{t-1} + \mathbf{I}^c \mathbf{x}_t + \mathbf{b}_c) \\
 \mathbf{m}_t &= \mathbf{g}^f \odot \mathbf{m}_{t-1} + \mathbf{g}^u \odot \mathbf{g}^c \\
 \mathbf{h}_t &= \tanh(\mathbf{g}^o \odot \mathbf{m}_t)
 \end{aligned} \tag{4.1}$$

where σ is the logistic sigmoid function, $\odot$ represents elementwise multiplication, $\mathbf{W}^u, \mathbf{W}^f, \mathbf{W}^o, \mathbf{W}^c$ are recurrent weight matrices, $\mathbf{I}^u, \mathbf{I}^f, \mathbf{I}^o, \mathbf{I}^c$ are projection matrices, $\mathbf{b}$ is the bias vector, and $\mathbf{h}$ and $\mathbf{m}$ are hidden and memory vectors responsible for controlling state updates and outputs [18]. On the other hand, the input to some unit x_i^l in layer l is the sum of the previous layer's cells contributions y multiplied by

a filter ω with size m [11]. More clearly,

$$x_i^l = \sum_{a=0}^m \omega_a y_{i+a}^{l-1} + b_i \quad (4.2)$$

Compared directly against the fundamental equations behind a 1D convolution layer, one can see a stark contrast in complexity. Even if the filter or the number of previous-layer inputs are large in size, the CNN model is significantly simpler than the RNN-LSTM model and thus is easier and faster to train.

The CNN also outperformed the RNN-LSTM model in classification capability. The RNN-LSTM model feeds the hidden layer from the previous layer from the previous step into the next step to provide information for tasks requiring long-range contextual information, but the input data here is based on short, simulated step responses. The additional computations aren't needed for classifying the data in this work; in fact, the RNN-LSTM is incorrectly biased on the built-up memory. The CNN is looking for specific patterns within windows of time within the time-series data. The clean, short simulated data does not vary in sequence length and has repeatable patterns within the data so the CNN is able to quickly train and accurately classify input data.

4.3 Future Work

This work laid down a foundation to explore an ANN-based TPMS, but much more work needs to be done before this technology can be applied. Future work should attempt to address the following aspects not covered here.

1. **Improve the simulated data.** In this work, all data was generated from a quarter-car model simulation. The simulation made many assumptions and is not representative of a real car model. A better simulation can be made by using a half-car or full-car model instead of a quarter-car model or making generally less assumptions.
2. **Collect experimental data.** Even better than simulated data is real exper-

imental data. Collecting and analyzing real data can result in a better, more generalized classifier with no issues arising from training on simulated data. Furthermore, the data should be generalized away from a step function profile to the acceleration profile of general driving such that the TPMS can identify underpressurized tires at all times.

3. **Develop the hardware.** Instead of assuming the computational and electrical power required for the system exists, a more-thorough investigation should be performed to determine the validity of the claim. A theoretical system with the properly specified requirements would bring this work one step closer to reality.
4. **Improve the algorithm.** Further fine-tuning the training parameters and hyperparameters as well as adding and removing layers and features from the model architecture may result in more efficient and effective models.

4.4 Conclusion

Considering the various limitations of the work, these ANN-based TPMSs are far away from being applied across the automotive industry. Nonetheless, this work showed that both a CNN and RNN-LSTM model can be developed and trained on simulated training data to accurately classify unseen simulation data. This proves the algorithm’s ability to identify unique patterns across each class and sort accordingly, all without any explicit instruction on the mechanical principles behind the data. With better data and appropriate hardware, vehicles may one day be equipped with ANN-based TPMS.

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APPENDICES

Appendix A

DERIVATIONS OF SIMULATION INPUT PARAMETERS

All constants used as simulation input variables are derived as follows. Except for identifying m_u , all of these calculations are performed in `CalculateTireStiffness.m` and `CalculateSuspensionStiffnessDamping.m`.

A.1 m_s

m_s is simply taken from [14] and divided by 4 to account for the quarter-car model.

$$m_s = 1109 \text{ kg} / 4 = 277.25 \text{ kg} \quad (\text{A.1})$$

A.2 k_s

Assuming that the tire in use across all vehicles is a radial-ply 165x13 tire (a very common tire size found on most passenger vehicles), a linear model for static stiffness based on tire inflation pressure can be used [30]. The model is graphically presented in Figure A.1 and expressed by equation A.2. The model is only accurate above 15 psi—an acceptable limitation as 15 psi is well below the threshold for “under-pressurized.”

$$k_s = 30.185p_u + 46.375 \quad (\text{A.2})$$

Figure A.1: Static stiffness vs. inflation pressure for a radial-ply car tire. [30]

A.3 m_u

Utilizing the average quarter-car ratio of the sprung to unsprung masses and the one can identify the expected value for m_u [16]:

$$\begin{aligned}
 \varepsilon = \frac{m_s}{m_u} = 8 &\Rightarrow m_u = \frac{m_s}{\varepsilon} \\
 &= \frac{277.25 \text{ kg}}{8} \\
 &= 34.69 \text{ kg}
 \end{aligned} \tag{A.3}$$

It should be noted that m_u should vary with tire pressure due to the additional air inside the tires. However, the mass of the air is insignificant relative to the rest of the unsprung mass ($< 0.1\%$). Nonetheless, the mass of the air is calculated and included in the unsprung mass for these simulations. The calculations are performed in `CalculateTireWeight.m`.

A.4 k_s and c_s

To identify the suspension's stiffness and damping coefficients, assume that the suspension is tuned for a properly-inflated tire. With $p_u = 32$ psi, equations A.2 and A.3 give the $k_u = 6979.53$ kPa and $m_u = 34.69$ kg respectively. With these values, one can find the natural frequency of the unsprung mass ω_u :

$$\begin{aligned}\omega_u &= \sqrt{\frac{k_u}{m_u}} \\ &= \sqrt{\frac{6979.53 \text{ kPa}}{34.69 \text{ kg}}} \\ &= 448.612 \text{ Hz}\end{aligned}\tag{A.4}$$

The average quarter-car ratio for sprung and unsprung natural frequencies is used to identify the sprung mass's natural frequency ω_s .

$$\begin{aligned}\alpha = \frac{\omega_s}{\omega_u} = 0.1 &\Rightarrow \omega_s = \alpha\omega_u \\ &= (0.1)(448.61 \text{ Hz}) \\ &= 44.86 \text{ Hz}\end{aligned}\tag{A.5}$$

We already know that $m_s = 277.25$ kg, so identifying k_s is trivial.

$$\begin{aligned}\omega_s = \sqrt{\frac{k_s}{m_s}} &\Rightarrow k_s = \omega_s^2 m_s \\ &= (44.86 \text{ Hz})^2 (277.25 \text{ kg}) \\ &= 557.97 \text{ kPa}\end{aligned}\tag{A.6}$$

To calculate c_s , we can use the relationship between ω_s and the damping ratio $\zeta = \frac{c_s}{c}$, where c is the critical damping coefficient. Numerous sources suggest the proper damping ratio in passenger vehicles to be between 0.2 and 0.3 [7] [10]. For this work, we define $\zeta = 0.25$.

$$\begin{aligned}
\zeta = \frac{c_s}{2m_s\omega_s} &\Rightarrow c_s = 2\zeta m_s\omega_s \\
&= 2(0.25)(277.25 \text{ kg})(44.86 \text{ Hz}) \\
&= 6218.8 \text{ Pa} \cdot \text{s}
\end{aligned} \tag{A.7}$$

Appendix B

SOURCE CODE

B.1 cnn_model.py

```
1  """Created on 24 June 2017.
2  @author: Alex Kost
3  @description: Main python code file for Applying CNN as a TPMS.
4  """
5
6  # Basic Python
7  import logging
8
9  # Extended Python
10 import tensorflow as tf
11
12 # Alex Python
13 from data_processor import SIM_LENGTH_SEQ
14
15
16 class CNNModel(object):
17     """
18     CNNModel is a class that builds and trains a CNN Model.
19
20     Attributes:
21         accuracy (TensorFlow operation): step accuracy (predictions vs. labels)
22         beta1 (float): exponential decay rate for the 1st moment estimates
23         beta2 (float): exponential decay rate for the 2nd moment estimates
24         cost (TensorFlow operation): cross entropy loss
25         dropout_rate (float): dropout rate; 0.1 == 10% of input units drop out
26         epsilon (float): a small constant for numerical stability
27         kernel_size (int): kernel size in conv layer
28         learning_rate (float): learning rate, used for optimizing
29         logger (logger object): logging object to write to stream/file
30         n_classes (int): number of classifications: under, nominal, over pressure
31         n_features (int): number of features in input feature data: sprung_accel
32         num_fc_1 (int): number of neurons in first fully connected layer
33         num_filt_1 (int): number of filters in conv layer
```

```

34         optimizer (TensorFlow operation): AdamOptimizer operation used to train
↪ the model
35         summary_op (TensorFlow operation): summary operation of all tf.summary
↪ objects
36         trainable (TensorFlow placeholder): boolean flag to separate
↪ training/evaluating
37         x (TensorFlow placeholder): input feature data
38         y (TensorFlow placeholder): input label data
39     """
40
41     def __init__(self):
42         """Constructor."""
43         # HYPERPARAMETERS
44         self.num_filt_1 = 16                                # number of filters in conv
↪ layer
45         self.kernel_size = 5                                # kernel size in conv layer
46         self.num_fc_1 = 30                                    # number of neurons in first
↪ fully connected layer
47         self.dropout_rate = 0.2                              # dropout rate; 0.1 == 10% of
↪ input units drop out
48         self.learning_rate = 0.001                          # learning rate, used for
↪ optimizing
49         self.beta1 = 0.9                                      # exponential decay rate for
↪ the 1st moment estimates
50         self.beta2 = 0.999                                    # exponential decay rate for
↪ the 2nd moment estimates
51         self.epsilon = 1e-08                                  # a small constant for
↪ numerical stability
52
53         # CONSTANT
54         self.n_features = 1                                    # sprung_accel
55         self.n_classes = 3                                    # classifications: under,
↪ nominal, over pressure
56         self.logger = logging.getLogger(__name__)            # get the logger!
57
58         # MODEL MEMBER VARIABLES
59         self.x = None                                          # input data
60         self.y = None                                          # input label
61         self.cost = None                                       # cross entropy loss
62         self.accuracy = None                                   # step accuracy (predictions
↪ vs. labels)
63         self.optimizer = None                                  # optimizing operation
64         self.trainable = tf.placeholder(tf.bool, name='trainable') # flag to
↪ separate training/evaluating

```

```

65         self.summary_op = None                                # summary operation to write
        ↪      data
66
67     def build_model(self):
68         """Build the CNN Model."""
69         input_shape = [None, SIM_LENGTH_SEQ, self.n_features] if self.n_features >
        ↪      1 else [None, SIM_LENGTH_SEQ]
70         self.x = tf.placeholder(tf.float32, shape=input_shape, name='input_data')
71         self.y = tf.placeholder(tf.int64, shape=[None], name='input_labels')
72
73         with tf.variable_scope("Reshape_Data"):
74             # tf.nn.conv2d requires inputs to be shaped as follows:
75             # [batch, in_height, in_width, in_channels]
76             # so -1 = batch size, should adapt accordingly
77             # in_height = "height" of the image (so one dimension)
78             # in_width = "width" of image
79             x_resaped = tf.reshape(self.x, [-1, SIM_LENGTH_SEQ, self.n_features])
80             self.logger.debug('Input dims: {}'.format(x_resaped.get_shape()))
81
82         with tf.variable_scope("ConvBatch1"):
83             x_bn = tf.contrib.layers.batch_norm(inputs=x_resaped,
84                                                 is_training=self.trainable,
85                                                 updates_collections=None)
86
87             conv1 = tf.layers.conv1d(inputs=x_bn,
88                                       filters=self.num_filt_1,
89                                       kernel_size=[self.kernel_size])
90             self.logger.debug('Conv1 output dims: {}'.format(conv1.get_shape()))
91
92         with tf.variable_scope("Fully_Connected1"):
93             conv2_flatten = tf.layers.flatten(conv1, name='Flatten')
94             fc1 = tf.contrib.layers.fully_connected(inputs=conv2_flatten,
95                                                     num_outputs=self.num_fc_1,
96
97                                                     ↪ weights_initializer=tf.contrib.layers.xavier_initializer(),
98                                                     ↪ biases_initializer=tf.constant_initializer(0.0),
99                                                     ↪ normalizer_fn=tf.contrib.layers.batch_norm,
100                                                     ↪ normalizer_params={'is_training':
101                                                         ↪ self.trainable,
102                                                         ↪ 'updates_collections':
103                                                         ↪ None})

```



```

101         fc1 = tf.layers.dropout(inputs=fc1, rate=self.dropout_rate,
102                                   ↪ training=self.trainable)
103         self.logger.debug('FCon1 output dims: {}'.format(fc1.get_shape()))
104     with tf.variable_scope("Fully_Connected2"):
105         pred = tf.contrib.layers.fully_connected(inputs=fc1,
106                                                    num_outputs=self.n_classes,
107                                                    ↪ weights_initializer=tf.contrib.layers.x
108                                                    ↪ biases_initializer=tf.constant_initiali
109         self.logger.debug('FCon2 output dims: {}'.format(pred.get_shape()))
110         tf.summary.histogram('pred', pred)
111
112     # MEASURE MODEL ERROR
113     # Cross-Entropy: "measuring how inefficient our predictions are for
114     ↪ describing the truth"
115     # http://colah.github.io/posts/2015-09-Visual-Information/
116     #
117     ↪ https://stackoverflow.com/questions/41689451/valueerror-no-gradients-provided-for-an
118     # Use sparse softmax because we have mutually exclusive classes
119     # logits must be [batch_size, num_classes], label must be [batch_size]
120     # tf.reduce_mean = reduces tensor to mean scalar value of tensor
121     with tf.variable_scope("Softmax"):
122         cross_entropy =
123             ↪ tf.nn.sparse_softmax_cross_entropy_with_logits(logits=pred,
124             ↪ labels=self.y)
125         self.cost = tf.reduce_mean(cross_entropy, name='cost')
126         tf.summary.scalar('cross_entropy_loss', self.cost)
127
128     # EVALUATE OUR MODEL
129     # tf.argmax = returns index of the highest entry in a tensor along some
130     ↪ axis.
131     # Predictions are probabilities corresponding to class (ex. [0.7 0.2
132     ↪ 0.1])
133     # tf.argmax returns the most probable label (ex. 0)
134     # tf.equal = compares prediction to truth, returns list of bools (T if
135     ↪ correct, F if not)
136     # tf.reduce_mean = reduces tensor to mean scalar value of tensor
137     # tf.cast = convert bools to 1 and 0
138     with tf.variable_scope("Evaluating"):
139         correct_pred = tf.equal(tf.argmax(pred, 1), self.y)
140         self.accuracy = tf.reduce_mean(tf.cast(correct_pred, tf.float32))
141         tf.summary.scalar('accuracy', self.accuracy)

```

```
136         # OPTIMIZE OUR MODEL
137         with tf.variable_scope("Optimizing"):
138             self.optimizer = tf.train.AdamOptimizer(self.learning_rate,
139                                                         beta1=self.beta1,
140                                                         beta2=self.beta2,
141                                                         ↪ epsilon=self.epsilon).minimize(self.cost)
```

B.2 rnn_model.py

```
1  """Created on 24 June 2017.
2  @author: Alex Kost
3  @description: Main python code file for Applying RNN as a TPMS.
4  """
5
6  # Basic Python
7  import logging
8
9  # Extended Python
10 import tensorflow as tf
11
12 # Alex Python
13 from data_processor import SIM_LENGTH_SEQ
14
15
16 class RNNModel(object):
17     """
18     RNNModel is a class that builds and trains a RNN model with LSTM cells.
19
20     Attributes:
21         accuracy (TensorFlow operation): step accuracy (predictions vs. labels)
22         beta1 (float): exponential decay rate for the 1st moment estimates
23         beta2 (float): exponential decay rate for the 2nd moment estimates
24         cost (TensorFlow operation): cross entropy loss
25         dropout_rate (float): dropout rate; 0.1 == 10% of input units drop out
26         epsilon (float): a small constant for numerical stability
27         learning_rate (float): learning rate, used for optimizing
28         logger (logger object): logging object to write to stream/file
29         n_classes (int): number of classifications: under, nominal, over pressure
30         n_features (int): number of features in input feature data: sprung_accel
31         n_hidden (int): number of features per hidden layer in RNN
32         n_layers (int): number of hidden layers in model
33         num_fc_1 (int): number of neurons in first fully connected layer
34         optimizer (TensorFlow operation): AdamOptimizer operation used to train
↪ the model
35         summary_op (TensorFlow operation): summary operation of all tf.summary
↪ objects
36         trainable (TensorFlow placeholder): boolean flag to separate
↪ training/evaluating
37         x (TensorFlow placeholder): input feature data
38         y (TensorFlow placeholder): input label data
```

```

39     """
40
41     def __init__(self):
42         """Constructor."""
43         # HYPERPARAMETERS
44         self.n_hidden = 8 # number of features per
45             ↳ hidden layer in LSTM
46         self.num_fc_1 = 16 # number of neurons in first
47             ↳ fully connected layer
48         self.n_layers = 2 # number of hidden layers in
49             ↳ model
50         self.dropout_rate = 0.5 # dropout rate; 0.1 == 10% of
51             ↳ input units drop out
52         self.learning_rate = 0.0001 # learning rate, used for
53             ↳ optimizing
54         self.beta1 = 0.9 # exponential decay rate for
55             ↳ the 1st moment estimates
56         self.beta2 = 0.999 # exponential decay rate for
57             ↳ the 2nd moment estimates
58         self.epsilon = 1e-08 # a small constant for
59             ↳ numerical stability
60
61         # CONSTANT
62         self.n_features = 1 # sprung_accel
63         self.n_classes = 3 # classifications: under,
64             ↳ nominal, over pressure
65         self.logger = logging.getLogger(__name__) # get the logger!
66
67         # MODEL MEMBER VARIABLES
68         self.x = None # input data
69         self.y = None # input label
70         self.cost = None # cross entropy loss
71         self.accuracy = None # step accuracy (predictions
72             ↳ vs. labels)
73         self.optimizer = None # optimizing operation
74         self.trainable = tf.placeholder(tf.bool, name='trainable') # flag to
75             ↳ separate training/evaluating
76         self.summary_op = None # summary operation to write
77             ↳ data
78
79     def build_model(self):
80         """Build the RNN model."""
81         input_shape = [None, SIM_LENGTH_SEQ, self.n_features] if self.n_features >
82             ↳ 1 else [None, SIM_LENGTH_SEQ]
83         self.x = tf.placeholder(tf.float32, shape=input_shape, name='input_data')

```

```

71     self.y = tf.placeholder(tf.int64, shape=[None], name='input_labels')
72
73     if input_shape == [None, SIM_LENGTH_SEQ]:
74         with tf.variable_scope("Reshape_Data"):
75             # tf.nn.conv2d requires inputs to be shaped as follows:
76             # [batch_size, max_time, ...]
77             # so -1 = batch size, should adapt accordingly
78             # max_time = SIM_LENGTH_SEQ
79             # ... = self.n_features
80             x_resaped = tf.reshape(self.x, [-1, SIM_LENGTH_SEQ,
81                 ↪ self.n_features])
82
83             self.logger.debug('Input dims: {}'.format(x_resaped.get_shape()))
84
85         with tf.variable_scope("LSTM_RNN"):
86             # add stacked layers if more than one layer
87             if self.n_layers > 1:
88                 cell = tf.contrib.rnn.MultiRNNCell([self._setup_lstm_cell() for _
89                 ↪ in range(self.n_layers)],
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108                                     ↪ biases_initializer=tf.constant_initializer
109                                     ↪ normalizer_fn=tf.contrib.layers.batch_norm
110                                     ↪ normalizer_params={'is_training':
111                                     ↪ self.trainable,
                                     ↪ 'updates_collections':
                                     ↪ None})
112
113     fc1 = tf.layers.dropout(inputs=fc1, rate=self.dropout_rate,
114                             ↪ training=self.trainable)
115     self.logger.debug('FCon1 output dims: {}'.format(fc1.get_shape()))
116
117     with tf.variable_scope("Fully_Connected2"):
118         pred = tf.contrib.layers.fully_connected(inputs=fc1,
119                                                  num_outputs=self.n_classes,
120                                                  ↪ weights_initializer=tf.contrib.layers.x
121                                                  ↪ biases_initializer=tf.constant_initializer
122         self.logger.debug('FCon2 output dims: {}'.format(pred.get_shape()))
123         tf.summary.histogram('pred', pred)
124
125     # MEASURE MODEL ERROR
126     # Cross-Entropy: "measuring how inefficient our predictions are for
127         ↪ describing the truth"
128     # http://colah.github.io/posts/2015-09-Visual-Information/
129     #
130         ↪ https://stackoverflow.com/questions/41689451/valueerror-no-gradients-provided-for-an
131     # Use sparse softmax because we have mutually exclusive classes
132     # logits must be [batch_size, num_classes], label must be [batch_size]
133     # tf.reduce_mean = reduces tensor to mean scalar value of tensor
134     with tf.variable_scope("Softmax"):
135         cross_entropy =
136         ↪ tf.nn.sparse_softmax_cross_entropy_with_logits(logits=pred,
137         ↪ labels=self.y)
138     self.cost = tf.reduce_mean(cross_entropy, name='total')
139     tf.summary.scalar('cross_entropy_loss', self.cost)
140
141     # EVALUATE OUR MODEL
142     # tf.argmax = returns index of the highest entry in a tensor along some
143         ↪ axis.

```

```

138     # Predictions are probabilities corresponding to class (ex. [0.7 0.2
        ↪ 0.1])
139     # tf.argmax returns the most probable label (ex. 0)
140     # tf.equal = compares prediction to truth, returns list of bools (T if
        ↪ correct, F if not)
141     # tf.reduce_mean = reduces tensor to mean scalar value of tensor
142     # tf.cast = convert bools to 1 and 0
143     with tf.variable_scope("Evaluating"):
144         correct_pred = tf.equal(tf.argmax(pred, 1), self.y)
145         self.accuracy = tf.reduce_mean(tf.cast(correct_pred, tf.float32))
146         tf.summary.scalar('accuracy', self.accuracy)
147
148     # OPTIMIZE OUR MODEL
149     with tf.variable_scope("Optimizing"):
150         self.optimizer = tf.train.AdamOptimizer(self.learning_rate,
151                                                    beta1=self.beta1,
152                                                    beta2=self.beta2,
153
154                                                    ↪ epsilon=self.epsilon).minimize(self.cost
155
156     """ Helper Functions """
157     def _setup_lstm_cell(self):
158
159         """Creates an LSTM Cell to be unrolled.
160
161         There's a bug in tf.contrib.rnn.MultiRNNCell that requires we create
162         new cells every time we want to a mult-layered RNN. So we use this
163         helper function to create a LSTM cell. See more here:
164         https://github.com/udacity/deep-learning/issues/132#issuecomment-325158949
165
166         Returns:
167         cell (BasicLSTMCell): BasicLSTM Cell
168         """
169         # forget_bias set to 1.0 b/c
170         ↪ http://proceedings.mlr.press/v37/jozefowicz15.pdf
171         cell = tf.nn.rnn_cell.BasicLSTMCell(self.n_hidden, forget_bias=1.0,
172                                             ↪ state_is_tuple=True)
173
174     return cell

```

B.3 data_processor.py

```
1  """Created on 17 December 2017.
2  @author: Alex Kost
3  @description: Main python code file for preprocessing data
4
5  Attributes:
6      SIM_DATA_PATH (str): Local simulation data output folder path
7      SIM_LENGTH_FIX (int): bias to datapoint length due to slicing ops in Matlab,
   ↪  datapoints
8      SIM_LENGTH_SEQ (int): simulation length, datapoints
9      SIM_LENGTH_TIME (float): simulation time, sec
10     SIM_RESOLUTION (float): simulation resolution, sec/datapoint
11 """
12
13 # Basic Python
14 import logging
15 import os
16
17 # Extended Python
18 import numpy as np
19
20 # Simulation Constants
21 SIM_LENGTH_TIME = 1.5 - .45
22 SIM_RESOLUTION = .001
23 SIM_LENGTH_FIX = 2
24 SIM_LENGTH_SEQ = int(SIM_LENGTH_TIME / SIM_RESOLUTION) + SIM_LENGTH_FIX
25 SIM_DATA_PATH = 'Data/simulated_labeled'
26
27
28 class DataProcessor(object):
29     """
30     DataProcessor is a class that processes datasets.
31
32     Attributes:
33         logger (logger object): logging object to write to stream/file
34         n_classes (int): number of classifications: under, nominal, over pressure
35         n_features (int): number of features in input feature data: sprung_accel
36         test_data (np.array): loaded data from test dataset
37         test_files (list of strings): list of filenames in test dataset
38         train_data (np.array): loaded data from training dataset
39         train_files (list of strings): list of filenames in training dataset
40         val_data (np.array): loaded data from validation dataset
```



```

41         val_files (list of strings): list of filenames in validation dataset
42     """
43     def __init__(self, n_classes, n_features):
44         """Constructor
45
46         Args:
47             n_classes (int): label classifications
48             n_features (int): features per example
49         """
50         # assign input variables
51         self.n_classes = n_classes
52         self.n_features = n_features
53
54         # FILENAME LISTS
55         self.train_files = []
56         self.val_files = []
57         self.test_files = []
58
59         # LOADED DATA
60         self.train_data = None
61         self.val_data = None
62         self.test_data = None
63
64         self.logger = logging.getLogger(__name__) # get the logger!
65
66     def preprocess_all_data(self):
67         """Shuffle all data and then preprocess the files."""
68         all_files = self._create_filename_list(SIM_DATA_PATH)
69         np.random.shuffle(all_files)
70
71         train_val_test_files = self._split_datafiles(all_files) # train_set,
72         ↪ val_set, test_set
73         self.train_files = train_val_test_files[0]
74         self.val_files = train_val_test_files[1]
75         self.test_files = train_val_test_files[2]
76
77         # Report sizes and load all datasets
78         self.logger.info('Train set size: %d', len(self.train_files))
79         self.logger.info('Validation set size: %d', len(self.val_files))
80         self.logger.info('Test set size: %d', len(self.test_files))
81         self._load_all_datasets()
82
83     def preprocess_data_by_label(self):
84         """Simulation data is organized by label. This method mixes and splits up
85         ↪ the data."""

```

```

84         for i in range(self.n_classes):
85             modified_data_path = os.path.join(SIM_DATA_PATH, str(i))
86             class_files = self._create_filename_list(modified_data_path)
87
88             # get files for each thing
89             result = self._split_datafiles(class_files)    # train_set, val_set,
90                 ↪ test_set
91             self.train_files.extend(result[0])
92             self.val_files.extend(result[1])
93             self.test_files.extend(result[2])
94             self.logger.debug('%d/%d/%d added to train/val/test set from class
95                 ↪ %d.',
96                                     len(result[0]), len(result[1]),
97                                     len(result[2]), i)
98
99             # Shuffle data
100             np.random.shuffle(self.train_files)
101             np.random.shuffle(self.val_files)
102             np.random.shuffle(self.test_files)
103
104             # Report sizes and load all datasets
105             self.logger.info('Train set size: %d', len(self.train_files))
106             self.logger.info('Validation set size: %d', len(self.val_files))
107             self.logger.info('Test set size: %d', len(self.test_files))
108             self._load_all_datasets()
109
110             """ Helper Functions """
111             def _load_all_datasets(self):
112                 """Assign class member variables after processing filenames."""
113                 self.train_data = self._load_data(self.train_files)    # features, labels
114                 self.val_data = self._load_data(self.val_files)          # features,
115                     ↪ labels
116                 self.test_data = self._load_data(self.test_files)        # features,
117                     ↪ labels
118
119             @staticmethod
120             def _create_filename_list(data_dir):
121                 """Identify the list of CSV files based on a given data_dir.
122
123                 Args:
124                     data_dir (string): local path to where the data is saved.
125
126                 Returns:
127                     filenames (list of strings): a list of CSV files found in the data
128                     ↪ directory

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```

124         """
125         filenames = []
126         for root, _, files in os.walk(data_dir):
127             for filename in files:
128                 if filename.endswith(".csv"):
129                     rel_filepath = os.path.join(root, filename)
130                     abs_filepath = os.path.abspath(rel_filepath)
131                     filenames.append(abs_filepath)
132
133         return filenames
134
135     @staticmethod
136     def _split_datafiles(data, val_size=0.2, test_size=0.2):
137         """Split all the data we have into training, validating, and test sets.
138
139         By default, 60/20/20 split
140         Credit:
141         ↪ https://www.slideshare.net/TaegyunJeon1/electricity-price-forecasting-with-recurrent-neural-
142
143         Args:
144             data (list): list of filenames
145             val_size (float, optional): Percentage of data to be used for
146             ↪ validation set
147             test_size (float, optional): Percentage to data set to be used for
148             ↪ test set
149
150         Returns:
151             train_set (list): list of training example filenames
152             val_set (list): list of validation example filenames
153             test_set (list): list of test example filenames
154         """
155         val_length = int(len(data) * val_size)
156         test_length = int(len(data) * test_size)
157
158         val_set = data[:val_length]
159         test_set = data[val_length:val_length + test_length]
160         train_set = data[val_length + test_length:]
161
162         return train_set, val_set, test_set
163
164     def _load_data(self, filenames):
165         """Load data from the filenames
166
167         Args:
168             filenames (list of strings): filenames

```

```

166
167     Returns:
168         features, labels (np.array, np.array): loaded features and labels
169     """
170     # Get features and labels from dataset
171     features, labels = [], []
172     for example_file in filenames:
173         example_data = np.loadtxt(example_file, delimiter=',')
174
175         ex_label = example_data[0, 0] if self.n_features > 1 else
            ↪ example_data[0]
176         ex_feature = example_data[:, 1:] if self.n_features > 1 else
            ↪ example_data[1:]
177
178         features.append(ex_feature)
179         labels.append(ex_label)
180
181     # stack features
182     features = np.vstack(features)
183
184     return features, labels

```

B.4 train.py

```
1  """Created on 24 June 2017.
2  @author: Alex Kost
3  @description: Training class for CNN and RNN models
4
5  Attributes:
6      DEFAULT_FORMAT (str): Logging format
7      LOGFILE_NAME (str): Logging file name
8      OUTPUT_DIR (str): TensorBoard output directory
9  """
10
11  # Basic Python
12  import logging
13  import os
14  from time import strftime
15  from math import ceil
16
17  # Extended Python
18  import progressbar
19  import tensorflow as tf
20
21  # Alex Python
22  from data_processor import DataProcessor
23  from rnn_model import RNNModel      # RNN MODEL
24  from cnn_model import CNNModel      # CNN MODEL
25
26  # Progressbar config
27  progressbar.streams.wrap_stderr()
28
29  # Constants
30  DEFAULT_FORMAT = '%(asctime)s: %(levelname)s: %(message)s'
31  LOGFILE_NAME = 'train.log'
32  OUTPUT_DIR = 'output'
33
34
35  class TrainModel(DataProcessor):
36      """
37      TrainModel is a class that builds and trains a provided model.
38
39      Attributes:
40          batch_size (int): number of examples in a single batch
41          dropout_rate (float): dropout rate; 0.1 == 10% of input units drop out
```

```

42     learning_rate (float): learning rate, used for optimizing
43     logger (logger object): logging object to write to stream/file
44     model (TensorFlow model object): Model to train and evaluate
45     n_checks (int): number of times to check performance while training
46     n_epochs (int): number of times we go through all data
47     summary_op (TensorFlow operation): summary operation of all tf.summary
↪ objects
48     """
49     def __init__(self, model, n_epochs=20, batch_size=32):
50         """Constructor.
51
52         Args:
53             model (TensorFlow model object): Model to train and evaluate
54             n_epochs (int, optional): number of times we go through all data
55             batch_size (int, optional): number of examples in a single batch
56         """
57         # TRAINING PARAMETERS
58         self.n_epochs = n_epochs
59         self.batch_size = batch_size
60
61         # CONSTANT
62         self.model = model
63         self.summary_op = None
64         self.logger = logging.getLogger(__name__)
65         self.n_checks = 5
66
67         # INPUT DATA/LABELS
68         super(TrainModel, self).__init__(self.model.n_classes,
↪         self.model.n_features)
69         self.preprocess_data_by_label()
70
71         # HELPER VARIABLES
72         self._ex_per_epoch = None
73         self._steps_per_epoch = None
74         self._train_length_ex = None
75         self._train_length_steps = None
76         self.calculate_helpers()
77
78     def calculate_helpers(self):
79         """Calculate helper variables for training length."""
80         self._ex_per_epoch = len(self.train_files)
81         self._steps_per_epoch = int(ceil(self._ex_per_epoch /
↪         float(self.batch_size)))
82         self._train_length_ex = self._ex_per_epoch * self.n_epochs
83         self._train_length_steps = self._steps_per_epoch * self.n_epochs

```

```

84
85     self.logger.debug('self._ex_per_epoch: %d', self._ex_per_epoch)
86     self.logger.debug('self._steps_per_epoch: %d', self._steps_per_epoch)
87     self.logger.debug('self._train_length_ex: %d', self._train_length_ex)
88     self.logger.debug('self._train_length_steps: %d',
89         ↪ self._train_length_steps)
90
91 def train_model(self, use_tensorboard=True):
92     """Train the model.
93
94     Args:
95
96     use_tensorboard (bool, optional): Description
97
98     Returns:
99
100     TYPE: Description
101     """
102
103     # SETUP TENSORBOARD FOR NEW RUN
104     if use_tensorboard:
105         checkpoint_prefix, run_dir = self._setup_tensorboard_directories()
106         saver = tf.train.Saver(tf.global_variables())
107     else:
108         self.logger.info('*** NEW RUN ***')
109         self._log_training_and_model_params()
110         self.summary_op = tf.summary.merge_all()
111
112     # TRAIN
113     with tf.Session() as sess:
114         # Initialization
115         progress_bar =
116         ↪ progressbar.ProgressBar(max_value=self._train_length_steps)
117         sess.run(tf.global_variables_initializer())
118         if use_tensorboard:
119             train_writer = tf.summary.FileWriter(run_dir + '/train',
120                 ↪ sess.graph)
121             val_writer = tf.summary.FileWriter(run_dir + '/val')
122             batch_idx = 0
123             progress_bar.start()
124             progress_bar.update(0)
125
126             self.logger.info("The training shall begin.")
127             try:
128                 _, acc_test_before, _ = self.evaluate_model_on_data(sess, 'test')
129                 for step in range(self._train_length_steps):
130                     # Reset/increment batch_idx

```

```

126         if step % self._steps_per_epoch == 0:
127             batch_idx = 0
128         else:
129             batch_idx += 1
130
131         if use_tensorboard:
132             do_full_eval = step % ceil(self._train_length_steps /
133                                     ↪ float(self.n_checks)) == 0
134             do_full_eval = do_full_eval or (step ==
135                                     ↪ self._train_length_steps - 1)
136             if do_full_eval:
137                 # Check training and validation performance
138                 cost_train, acc_train, _ =
139                 ↪ self.evaluate_model_on_data(sess, 'train')
140                 cost_val, acc_val, summary =
141                 ↪ self.evaluate_model_on_data(sess, 'val')
142
143                 # Report information to user
144                 self.logger.info('%d epochs elapsed.', step /
145                 ↪ self._steps_per_epoch)
146                 self.logger.info('COST:      Train: %5.3f / Val:
147                 ↪ %5.3f', cost_train, cost_val)
148                 self.logger.info('ACCURACY: Train: %5.3f / Val:
149                 ↪ %5.3f', acc_train, acc_val)
150
151                 # Save to Tensorboard
152                 val_writer.add_summary(summary, step)
153                 saver.save(sess, checkpoint_prefix, global_step=step)
154
155                 ## If model is not learning immediately, break out of
156                 ↪ training
157                 # if acc_val == acc_test_before and step > 100:
158                 #     self.logger.info('Stuck on value: %d', acc_val)
159                 #     break
160
161                 # Training step
162                 x_batch, y_batch = self._generate_batch(batch_idx)
163                 _, summary = sess.run([self.model.optimizer, self.summary_op],
164                                     ↪ feed_dict={self.model.x: x_batch,
165                                     ↪ self.model.y: y_batch,
166                                     ↪ self.model.trainable: True})
167
168                 # Save to Tensorboard, update progress bar
169                 if use_tensorboard:
170                     train_writer.add_summary(summary, step)

```



```

163         progress_bar.update(step)
164     except KeyboardInterrupt:
165         self.logger.info('Keyboard Interrupt? Gracefully quitting.')
166     finally:
167         progress_bar.finish()
168         _, acc_test_after, _ = self.evaluate_model_on_data(sess, 'test')
169         self.logger.info("The training is done.")
170         self.logger.info('Test accuracy before training: %.3f.',
171             ↪ acc_test_before)
172         self.logger.info('Test accuracy after training: %.3f.',
173             ↪ acc_test_after)
174         if use_tensorboard:
175             train_writer.close()
176             val_writer.close()
177
178     return acc_test_after
179
180 def evaluate_model_on_data(self, sess, dataset_label):
181     """Evaluate the model on the entire training data.
182
183     Args:
184
185     sess (tf.Session object): active session object
186     dataset_label (string): dataset label
187
188     Returns:
189
190     float, float: the cost and accuracy of the model based on the dataset.
191     """
192     try:
193         dataset_dict = {'test': self.test_data,
194             ↪ 'train': self.test_data,
195             ↪ 'val': self.val_data}
196         dataset = dataset_dict[dataset_label]
197     except KeyError:
198         raise "dataset" arg must be in dataset dict:
199             ↪ '{}'.format(dataset_dict.keys())
200
201     cost, acc, summary = sess.run([self.model.cost, self.model.accuracy,
202         ↪ self.summary_op],
203
204                                     feed_dict={self.model.x: dataset[0],
205                                                 self.model.y: dataset[1],
206                                                 self.model.trainable: False})
207
208     return cost, acc, summary
209
210 @staticmethod

```

```

204     def reset_model():
205         """Reset the model to prepare for next run."""
206         tf.reset_default_graph()
207
208         """ Helper Functions """
209     def _setup_tensorboard_directories(self):
210         """Set up TensorBoard directories.
211
212         Returns:
213             checkpoint_prefix, run_dir (string, string): checkpoint prefix, output
214             → root folder
215         """
216         timestamp = str(strftime("%Y.%m.%d-%H.%M.%S"))
217         model_type = self.model.__class__.__name__.replace('Model', '')
218         model_name = timestamp + '_' + model_type
219         out_dir = os.path.abspath(os.path.join(os.path.curdir, OUTPUT_DIR))
220         run_dir = os.path.abspath(os.path.join(out_dir, model_name))
221         checkpoint_dir = os.path.abspath(os.path.join(run_dir, "checkpoints"))
222         checkpoint_prefix = os.path.join(checkpoint_dir, "model")
223         if not os.path.exists(checkpoint_dir):
224             os.makedirs(checkpoint_dir)
225
226         # Logging the Run
227         self.logger.info('*** NEW RUN ***')
228         self.logger.info('filename: %s', model_name)
229
230         return checkpoint_prefix, run_dir
231
232     def _log_training_and_model_params(self):
233         """Record new run details."""
234         model_type = self.model.__class__.__name__
235
236         self.logger.info(' *** TRAINING ***')
237         self.logger.info('     n_epochs: %d', self.n_epochs)
238         self.logger.info('     batch_size: %d', self.batch_size)
239         self.logger.info(' *** MODEL ***')
240         if 'CNN' in model_type:
241             self.logger.info('     num_filt_1: %d', self.model.num_filt_1)
242             self.logger.info('     kernel_size: %d', self.model.kernel_size)
243             self.logger.info('     num_fc_1: %d', self.model.num_fc_1)
244         elif 'RNN' in model_type:
245             self.logger.info('     n_hidden: %d', self.model.n_hidden)
246             self.logger.info('     num_fc_1: %d', self.model.num_fc_1)
247             self.logger.info('     n_layers: %d', self.model.n_layers)

```

```

248         self.logger.info('    dropout_rate: %f', self.model.dropout_rate)
249         self.logger.info('    learning_rate: %f', self.model.learning_rate)
250         self.logger.info('    beta1: %f', self.model.beta1)
251         self.logger.info('    beta2: %f', self.model.beta2)
252         self.logger.info('    epsilon: %f', self.model.epsilon)
253
254     def _generate_batch(self, batch_idx):
255         """Generate a batch and increment the sliding batch window within the
        ↪ data."""
256         features = self.train_data[0]
257         labels = self.train_data[1]
258
259         start_idx = batch_idx * self.batch_size
260         end_idx = start_idx + self.batch_size - 1
261
262         # Error handling for if sliding window goes beyond data list length
263         if end_idx > self._ex_per_epoch:
264             end_idx = self._ex_per_epoch
265
266         if self.n_features > 1:
267             x_batch = features[:, start_idx:end_idx]
268         else:
269             x_batch = features[start_idx:end_idx]
270
271         y_batch = labels[start_idx:end_idx]
272         self.logger.debug('batch_idx: %d', batch_idx)
273         self.logger.debug('Got training examples %d to %d', start_idx, end_idx)
274
275         return x_batch, y_batch
276
277
278     def main():
279         """Sup Main!"""
280         models = [CNNModel(), RNNModel()]
281         for model in models:
282             model.build_model()
283             train = TrainModel(model, n_epochs=200, batch_size=128)
284             train.train_model()
285             train.reset_model()
286
287
288     if __name__ == '__main__':
289         # create logger with 'spam_application'
290         logger = logging.getLogger()
291         logger.setLevel(logging.DEBUG)

```

```
292     # create file handler which logs even debug messages
293     fh = logging.FileHandler(LOGFILE_NAME)
294     fh.setLevel(logging.INFO)
295     # create console handler with a higher log level
296     ch = logging.StreamHandler()
297     ch.setLevel(logging.INFO)
298     # create formatter and add it to the handlers
299     formatter = logging.Formatter(DEFAULT_FORMAT)
300     fh.setFormatter(formatter)
301     ch.setFormatter(formatter)
302     # add the handlers to the logger
303     logger.addHandler(fh)
304     logger.addHandler(ch)
305
306     main()
```

B.5 tune.py

```
1  """Created on 6 Jan 2017.
2  @author: Alex Kost
3  @description: mastermind tuning script for model
4
5  Attributes:
6      DEFAULT_FORMAT (str): Logging format
7      LOGFILE_NAME (str): Logging file name
8      OUTPUT_DIR (str): TensorBoard output directory
9  """
10
11  # Basic Python
12  import logging
13
14  # Extended Python
15  from sigopt import Connection
16
17  # Alex Python
18  from train import TrainModel
19  from rnn_model import RNNModel      # RNN MODEL
20  from cnn_model import CNNModel      # CNN MODEL
21
22  # Constants
23  DEFAULT_FORMAT = '%(asctime)s: %(levelname)s: %(message)s'
24  LOGFILE_NAME = 'tune.log'
25  #EXPERIMENT_ID = 34189           # CNNModel Accuracy v1
26  #EXPERIMENT_ID = 34205           # CNNModel Accuracy v2
27  #EXPERIMENT_ID = 34424           # CNNModel Accuracy v3
28
29  EXPERIMENT_ID = 34631             # RNNModel Accuracy v1
30
31
32  class SigOptTune(object):
33      def __init__(self):
34          """Constructor."""
35          self.logger = logging.getLogger(__name__)    # get the logger!
36
37          self.conn =
38              ↳ Connection(client_token="XWCROUDALHMNJFABTLYVXBUIHISZQKKACUGULCENHPSZNQPSD")
39          self.experiment = None
40          self.suggestion = None
```

```

41
42     self.model = None
43     self.acc = None
44
45     def create_cnn_experiment(self):
46         """Create experiment. Modify as needed."""
47         self.experiment = self.conn.experiments().create(
48             name="CNNModel Accuracy v3",
49             parameters=[dict(name="learning_rate",
50                             bounds=dict(min=0.00001, max=0.1),
51                             type="double"),
52                         dict(name="dropout_rate",
53                             bounds=dict(min=0.2, max=0.9),
54                             type="double"),
55                         dict(name="beta1",
56                             bounds=dict(min=0.0001, max=0.999),
57                             type="double"),
58                         dict(name="beta2",
59                             bounds=dict(min=0.0001, max=0.999),
60                             type="double"),
61                         dict(name="epsilon",
62                             bounds=dict(min=1e-8, max=1.0),
63                             type="double"),
64                         dict(name="num_filt_1",
65                             bounds=dict(min=1, max=40),
66                             type="int"),
67                         dict(name="kernel_size",
68                             bounds=dict(min=1, max=10),
69                             type="int"),
70                         dict(name="num_fc_1",
71                             bounds=dict(min=1, max=40),
72                             type="int")
73                     ])
74
75         self.logger.info('Experiment created! ID %d.', self.experiment.id)
76
77     def create_rnn_experiment(self):
78         """Create experiment. Modify as needed."""
79         self.experiment = self.conn.experiments().create(
80             name="RNNModel Accuracy v1",
81             parameters=[dict(name="learning_rate",
82                             bounds=dict(min=0.00001, max=0.1),
83                             type="double"),
84                         dict(name="dropout_rate",
85                             bounds=dict(min=0.2, max=0.9),

```

```

86         type="double"),
87     dict(name="beta1",
88         bounds=dict(min=0.0001, max=0.999),
89         type="double"),
90     dict(name="beta2",
91         bounds=dict(min=0.0001, max=0.999),
92         type="double"),
93     dict(name="epsilon",
94         bounds=dict(min=1e-8, max=1.0),
95         type="double"),
96     dict(name="n_hidden",
97         bounds=dict(min=1, max=40),
98         type="int"),
99     dict(name="num_fc_1",
100         bounds=dict(min=1, max=40),
101         type="int"),
102     dict(name="n_layers",
103         bounds=dict(min=1, max=10),
104         type="int")
105 ])
106
107 self.logger.info('Experiment created! ID %d.', self.experiment.id)
108
109 def get_suggestions(self):
110     """Create suggestions for next iteration."""
111     try:
112         self.suggestion =
113             ↪ self.conn.experiments(EXPERIMENT_ID).suggestions().create()
114         logger.info('Created new suggestions.')
115     except:
116         ↪ self.conn.experiments(EXPERIMENT_ID).suggestions().delete(state="open")
117         self.suggestion =
118             ↪ self.conn.experiments(EXPERIMENT_ID).suggestions().create()
119         logger.info('Deleted old and created new suggestions.')
120
121 def update_parameters(self):
122     """Update model parameters with suggestions."""
123     #model_type = self.model.__class__.__name__.replace('Model', '')
124
125     params = self.suggestion.assignments
126     # if model_type == 'CNN':
127     #     self.model.num_filt_1 = int(params['num_filt_1'])
128     #     self.model.kernel_size = int(params['kernel_size'])
129     #     self.model.num_fc_1 = int(params['num_fc_1'])

```

```

128         # elif model_type == 'RNN':
129         #     self.model.n_hidden = int(params['n_hidden'])
130         #     self.model.num_fc_1 = int(params['num_fc_1'])
131         #     self.model.n_layers = int(params['n_layers'])
132
133         self.model.dropout_rate = params['dropout_rate']
134         self.model.learning_rate = params['learning_rate']
135         self.model.beta1 = params['beta1']
136         self.model.beta2 = params['beta2']
137         self.model.epsilon = params['epsilon']
138
139     def report_observation(self):
140         """Report observation to SigOpt."""
141         self.conn.experiments(EXPERIMENT_ID).observations().create(
142             suggestion=self.suggestion.id,
143             value=float(self.acc),
144             value_stddev=0.05)
145
146     def optimization_loop(self, model):
147         """Optimize the parameters based on suggestions."""
148         for i in range(100):
149             self.logger.info('Optimization Loop Count: %d', i)
150
151             # assign suggestions to parameters and hyperparameters
152             self.get_suggestions()
153
154             # update model class
155             self.model = model()
156             self.update_parameters()
157             self.model.build_model()
158
159             # update training class
160             train = TrainModel(self.model, n_epochs=200, batch_size=128)
161
162             # run the training stuff
163             self.acc = train.train_model()
164             train.reset_model()
165
166             # report to SigOpt
167             self.report_observation()
168
169
170 class GridSearchTune(object):
171     def __init__(self):
172         """Constructor."""

```



```

173         self.logger = logging.getLogger(__name__)    # get the logger!
174
175     def tune_cnn_with_gridsearch():
176         """Grid search to identify best hyperparameters for CNN model."""
177         cnn_model_values = []
178         n_epoch_list = [100, 200, 300, 400, 500]      #
179         ↪ 5
180         batch_size_list = [16, 32, 64, 128, 256]      #
181         ↪ 5
182         learning_rate_list = [.0001, .0005, .00001, .00005]  #
183         ↪ 4
184         dropout_rate_list = [0.2, 0.5, 0.7]          #
185         ↪ 3
186
187     try:
188         for n_epoch in n_epoch_list:
189             for batch_size in batch_size_list:
190                 for learning_rate in learning_rate_list:
191                     for dropout_rate in dropout_rate_list:
192                         for num_filt_1 in [8, 16, 32]:      # CNN ONLY
193                             ↪ # 3
194                             for num_filt_2 in [10, 20, 30, 40]:  # CNN ONLY
195                                 ↪ # 4
196                                 for num_fc_1 in [10, 20, 30, 40]:  # CNN ONLY
197                                     ↪ # 4
198                                     CNN = TrainModel(CNNModel, n_epoch,
199                                                         ↪ batch_size, learning_rate,
200                                                         ↪ dropout_rate)
201                                     CNN.model.num_filt_1 = num_filt_1
202                                     CNN.model.num_filt_2 = num_filt_2
203                                     CNN.model.num_fc_1 = num_fc_1
204                                     CNN.model.build_model()
205                                     CNN.calculate_helpers()
206                                     acc = CNN.train_model()
207                                     CNN.reset_model()
208
209                                     results = [acc, n_epoch, batch_size,
210                                                         ↪ learning_rate, dropout_rate,
211                                                         ↪ num_filt_1, num_filt_2, num_fc_1]
212                                     cnn_model_values.append(results)
213
214     except:
215         pass
216     finally:
217         best_cnn_run = max(cnn_model_values, key=lambda x: x[0])
218         logger.info('Best CNN run: {}'.format(best_cnn_run))

```

```

207         logger.info('All CNN runs: {}'.format(cnn_model_values))
208
209     def tune_rnn_with_gridsearch():
210         """Grid search to identify best hyperparameters for RNN."""
211         rnn_model_values = []
212         n_epoch_list = [200, 400, 600, 800, 1000] #
213         ↪ 5
214         batch_size_list = [16, 32, 64, 128, 256] #
215         ↪ 5
216         learning_rate_list = [.001, .005, .0001, .0005] #
217         ↪ 4
218         dropout_rate_list = [0.2, 0.5, 0.7] #
219         ↪ 3
220
221     for n_epoch in n_epoch_list:
222         for batch_size in batch_size_list:
223             for learning_rate in learning_rate_list:
224                 for dropout_rate in dropout_rate_list:
225                     for n_hidden in [8, 16, 32]: # RNN ONLY
226                         for num_fc_1 in [10, 20, 30, 40]: # RNN ONLY
227                             for n_layers in [1, 2, 3]: # RNN ONLY
228                                 RNN = TrainModel(RNNModel, n_epoch,
229                                     ↪ batch_size, learning_rate, dropout_rate)
230                                 RNN.model.n_hidden = n_hidden
231                                 RNN.model.num_fc_1 = num_fc_1
232                                 RNN.model.n_layers = n_layers
233
234                                 RNN.model.build_model()
235                                 RNN.calculate_helpers()
236                                 acc = RNN.train_model()
237                                 RNN.reset_model()
238
239                                 rnn_model_values.append([acc, n_epoch,
240                                     ↪ batch_size, learning_rate, dropout_rate,
241                                     ↪ n_hidden, num_fc_1, n_layers])
242
243     best_rnn_run = max(rnn_model_values, key=lambda x: x[0])
244     logger.info('Best RNN run: {}'.format(best_rnn_run))
245     logger.info('All RNN runs: {}'.format(rnn_model_values))
246
247 def main():
248     """Sup Main!"""
249     tune = SigOptTune()
250     #tune.create_cnn_experiment()

```

```

245     #tune.optimization_loop(CNNModel)
246     #tune.create_rnn_experiment()
247     tune.optimization_loop(RNNModel)
248
249 if __name__ == '__main__':
250     # create logger with 'spam_application'
251     logger = logging.getLogger()
252     logger.setLevel(logging.INFO)
253     # create file handler which logs even debug messages
254     fh = logging.FileHandler(LOGFILE_NAME)
255     fh.setLevel(logging.INFO)
256     # create console handler with a higher log level
257     ch = logging.StreamHandler()
258     ch.setLevel(logging.INFO)
259     # create formatter and add it to the handlers
260     formatter = logging.Formatter(DEFAULT_FORMAT)
261     fh.setFormatter(formatter)
262     ch.setFormatter(formatter)
263     # add the handlers to the logger
264     logger.addHandler(fh)
265     logger.addHandler(ch)
266
267     main()

```

B.6 main.m

```
1  %% Quarter Model Simulation MAIN
2  % Alex Kost
3  % Thesis
4  %
5  % Main file for quarter model simulation procedure.
6  %
7  % Arguments (see 'Test Parameters' section):
8  %   num_psis = num of psis to simulate
9  %   psi_min = minimum PSI to simulate
10 %   psi_max = maximum PSI to simulate
11 %   num_steps = num of step sizes to simulate
12 %   step_min = minimum step size to simulate
13 %   step_max = maximum step size to simulate
14 %   sim_tim = how long to run the simulation
15 %   snr = signal-to-noise ratio per sample, dB
16 %   save_path = path to save the simulation data
17 %
18 % Simulation data will output as plots and CSVs
19
20 %% Reset workspace and hide figures
21 clc
22 clear all
23 close all
24 set(0, 'DefaultFigureVisible', 'off');
25 set(0, 'DefaultFigureWindowStyle', 'docked');
26
27 %% Test parameters (user-provided)
28 num_psi = 25;           % number of psis to simulate
29 psi_min = 25.5;         % minimum psi
30 psi_max = 38.5;         % maximum psi
31
32 num_steps = 39;         % number of step sizes to simulate
33 step_min = .1;          % minimum step size, m
34 step_max = 2;           % maximum step size, m
35
36 sim_time = 1.5;         % simulation time, s
37 snr = 0;                % signal-to-noise ratio per sample, dB
38
39 % save data path
40 save_path = '/Users/alexkost/Dropbox/Grad Life/thesis/Data/simulated_labeled/';
41 %% Test parameters (predefined)
```

```

42 % Create a range of PSIs and Steps using defined values above
43 psi_all = linspace(psi_min, psi_max, num_psi);
44 steps_all = linspace(step_min, step_max, num_steps);
45
46 % ICs for simulations (cannot be nested in functions)
47 IC = [-1.74412834455962e-12
48        -2.44861738501480e-06
49        -5.70054231468026e-11
50        -7.99748963336152e-05];
51
52 %% Run simulations and get outputs (CSVs and plots)
53 for i=1:num_steps
54     step_size = steps_all(i);
55     figure(i)
56     hold on;
57     for j=1:num_psi
58         % run simulation
59         psi = psi_all(j);
60         simout = QuarterModelSimulation(psi, ...
61                                         step_size, ...
62                                         sim_time);
63
64         % Add white gaussian noise if snr > 0
65         if snr > 0
66             for k=1:size(simout, 2)
67                 simout(:,k) = awgn(simout(:, k), snr);
68             end
69         end
70
71         % interpret simulation outputs
72         sprung_pos = simout(:,1);
73         %sprung_vel = simout(:,2);
74         %unsprung_pos = simout(:,3);
75         %unsprung_vel = simout(:,4);
76         step = simout(:,5);           % constant every run
77         time = simout(:,6);           % constant every run
78         sprung_acc = simout(:,7);
79         %unsprung_acc = simout(:,8);
80
81         % Plot individual run
82         str = strcat(num2str(psi, '%.1f'), ' psi');
83         plot(time, sprung_pos, 'DisplayName', str);
84
85         % calculate label value
86         if psi < 30

```

```

87         label_val = 0;
88     elseif psi <= 34
89         label_val = 1;
90     elseif psi > 34
91         label_val = 2;
92     end
93
94     % Output to CSV
95     % Modifications done for Tensorflow
96     %     use sprung acceleration data only (1 feature)
97     %     transpose so each row is independent example
98     %     remove first .45 seconds of data
99     filename = strcat('Sim_', ...
100                     num2str(psi, '%.1f'), 'psi_', ...
101                     num2str(step_size, '%.2f'), 'm.csv');
102     fullfilename = fullfile(save_path, num2str(label_val), filename);
103     acc_transposed = [sprung_acc]';
104     M = acc_transposed(:, (.45/.001):end);
105     label_val_column = ones(size(M, 1), 1) * label_val;
106     csvwrite(fullfilename, horzcat(label_val_column, M));
107 end
108
109 % create figure with step
110 plot(time, step, '--', 'DisplayName', 'Step');
111 hold off;
112 title(sprintf('Quarter-Car Motion\nStep size = %g [m]', step_size));
113 xlabel('Time (s)');
114 ylabel('Vehicle height (m)');
115 legend('show');
116
117 % save figure
118 filename = sprintf('Plot_step_size_%g.png', step_size);
119 fullfilename = fullfile(save_path, filename);
120 print(figure(i), fullfilename, '-dpng', '-r300');
121 end

```

B.7 QuarterModelSimulation.m

```
1 function [ simout ] = QuarterModelSimulation(psi, y, sim_time)
2 % QuarterModelSimulation runs a Simulink model based on provided PSI
3 % and outputs the relevant data to be used elsewhere
4
5 global m_s m_u c_s k_s k_u g alpha zeta
6
7 %% Constants
8 N_over_lb = 4.448;      % [N / lb]
9 m_over_in = .0254;     % [m / in]
10 m_over_mm = .001;      % [m /mm]
11 Pa_over_psi = 6894.76; % [Pa / psi]
12 g = 9.81;              % gravity, m/s^2
13
14 %% Vehicle parameters (user-provided)
15 m_s_full = 1109;        % full body mass, kg
16 zeta = .25;             % dampening ratio
17 epsilon = 8;            % sprung/unsprung mass ratio
18 alpha = .1;            % natural frequency ratio
19
20 %% Vehicle parameters (calculated)
21 m_s = m_s_full / 4;     % quarter body mass, kg
22 m_air = CalculateTireWeight(psi); % mass of air in tire, kg
23 m_u = (m_s / epsilon) + m_air; % quarter unsprung mass, kg
24
25 %% Calculate suspension values from ideal conditions (32 psi)
26 Pa_over_psi = 6894.76; % [Pa / psi]
27 k_u_eng = 30.185 * psi + 46.375; % unsprung stiffness, lb/in
28 k_u = k_u_eng * Pa_over_psi; % unsprung stiffness, N/m
29 omega_u = sqrt(k_u/m_u); % unsprung natural freq, Hz
30 k_s = alpha^2 * m_s * omega_u^2; % sprung stiffness, N/m
31 omega_s = sqrt(k_s/m_s); % sprung natural freq, Hz
32 c_s = 2 * zeta * sqrt(k_s * m_s); % spring damping, N/(m/s)
33
34
35 [ k_s, c_s, omega_s ] = CalculateSuspensionStiffnessDamping(32);
36
37 %% Calculate tire stiffness from PSI
38 % Unsprung mass refers to all masses that are attached to and not supported by the
   % ↪ spring, such as wheel, axle, or brakes.
39 [ k_u, omega_u ] = CalculateTireStiffness(psi);
40
```

```

41  %% Check we have all the values we need for the simulation
42  debug = 0;
43  if debug
44      fprintf('psi = %f [psi]\n', psi);
45      fprintf('step_size = %f [m]\n', y);
46      fprintf('m_s = %f [kg]\n', m_s);
47      fprintf('m_u = %f [kg]\n', m_u);
48      fprintf('c_s = %f [N/(m/s)]\n', c_s);
49      fprintf('k_s = %f [N/m]\n', k_s);
50      fprintf('k_u = %f [N/m]\n', k_u);
51      fprintf('g = %f [m/s^2]\n', g);
52      % And print out the stuff that we don't need anyways
53      fprintf('omega_s = %f [Hz]\n', omega_s);
54      fprintf('omega_u = %f [Hz]\n', omega_u);
55  end
56
57  %% run Simulink simulation
58  sim('QuarterModelMatrix.slx', sim_time);
59
60  end

```

B.8 CalculateSuspensionStiffnessDamping.m

```
1 function [ k_s, c_s, omega_s ] = CalculateSuspensionStiffnessDamping(psi)
2 % Function to identify stiffness and damping coefficients based on tire psi
3 % Other important parameters are defined by globals
4 global m_s m_u alpha zeta
5
6 %% Constants
7 Pa_over_psi = 6894.76; % [Pa / psi]
8
9 %% Calculations
10 k_u_eng = 30.185*psi + 46.375; % unsprung stiffness, lb/in
11 k_u = k_u_eng * Pa_over_psi; % unsprung stiffness, N/m
12 omega_u = sqrt(k_u/m_u); % unsprung natural freq, Hz
13 k_s = alpha^2 * m_s * omega_u^2; % sprung stiffness, N/m
14 omega_s = sqrt(k_s/m_s); % sprung natural freq, Hz
15 c_s = 2 * zeta * sqrt(k_s * m_s); % spring damping, N/(m/s)
16
17 end
```

B.9 CalculateTireStiffness.m

```
1 function [ k_u, omega_u ] = CalculateTireStiffness(psi)
2 % Function to identify stiffness and damping coefficients based on tire psi
3 % Other important parameters are defined by globals
4 global m_u
5
6 %% Constants
7 Pa_over_psi = 6894.76; % [Pa / psi]
8
9 %% Calculations
10 k_u_eng = 30.185*psi + 46.375; % unsprung stiffness, lb/in
11 k_u = k_u_eng * Pa_over_psi; % unsprung stiffness, N/m
12 omega_u = sqrt(k_u/m_u); % unsprung natural freq, Hz
13
14 end
```

B.10 SimFunc.m

```
1 function [ xDD ] = SimFunc(u)
2 % SimFunc is used in QuarterModelMatrix.slx
3 % All motions of equation are in matrix form and done here to keep
4 % the simulink model clean. GUIs can be painful sometimes.
5
6 global m_s m_u c_s k_s k_u g
7
8 % Reassign Simulink values for readability
9 x_s = u(1);           % sprung mass height, m
10 x_s_d = u(2);         % sprung mass velocity, m/s
11 x_u = u(3);           % unsprung mass height, m
12 x_u_d = u(4);         % unsprung mass velocity, m/s
13 y = u(5);             % road height (step input), m
14
15 % Assign matrix elements
16 M11 = m_s;
17 M12 = 0;
18 M21 = 0;
19 M22 = m_u;
20
21 C11 = c_s;
22 C12 = -c_s;
23 C21 = -c_s;
24 C22 = c_s;
25
26 K11 = k_s;
27 K12 = -k_s;
28 K21 = -k_s;
29 K22 = k_s + k_u;
30
31 F11 = m_u*(-g);
32 F21 = k_u*y + m_s*(-g);
33
34 % Assemble matrices
35 M = [M11 M12;
36      M21 M22];
37
38 C = [C11 C12;
39      C21 C22];
40
41 K = [K11 K12;
```

```

42         K21 K22];
43
44     F = [F11;
45         F21];
46
47     X_d = [x_s_d;
48           x_u_d];
49
50     X = [x_s;
51         x_u];
52
53     % Assemble the matrix form of the equation of motion
54     A = F - (C*X_d) - (K*X);
55
56     % Calculating x_s_ddot and x_u_ddot
57     % https://www.mathworks.com/help/matlab/ref/mldivide.html
58     xDD = M\A;
59
60     % % Equation form
61     % F_s = -k_s*(x_s - x_u) - c_s*(x_s_d - x_u_d);
62     % F_u = k_s*(x_s - x_u) + c_s*(x_s_d - x_u_d) - k_u*(x_u - y);
63     %
64     % xDD = [F_s/m_s;
65     %       F_u/m_u];
66
67     end

```

B.11 QuarterModelMatrix.slx

Figure B.1: QuarterModelMatrix.slx