DISH: DEMOCRACY IN STATE HOUSES

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Master of Science in Computer Science

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ABSTRACT

DiSH: Democracy in State Houses

Nicholas Russo

In our current political climate, state level legislators have become increasingly important. Due to cuts in funding and growing focus at the national level, public oversight for these legislators has drastically decreased. This makes it difficult for citizens and activists to understand the relationships and commonalities between legislators. This thesis provides three contributions to address this issue. First, we created a data set containing over 1200 features focused on a legislator’s activity on bills. Second, we created embeddings that represented a legislator’s level of activity and engagement for a given bill using a custom model called Democracy2Vec. Third, we provided a case study focused on the 2015-2016 California State Legislator and had our results verified by a political expert. Our results show that our embeddings can explain relationships between legislator and how they will likely act during the legislative process.

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Chapter 1

INTRODUCTION

1.1 Motivation

In our current political climate, the importance of state-level legislatures has grown tremendously. As the federal government continues to turn more partisan, there is a gridlock between the two opposing parties. This makes pushing any piece of legislation to completion difficult, all the while, state legislatures have gone in the opposite direction. In 2019, 49 of the 50 states will be controlled by one party[7]. This allows state legislators to be more bold in the type of legislation they present, especially in states whose legislature is comfortably controlled by one party. As a result, state legislation serves as trial runs and test cases for federal-level legislators hoping to propose similar legislation. Although these state legislatures have grown to be even more important, the level of public oversight and coverage has decreased dramatically[15][6][8]. Large media companies have become hyper focused on the national level of politics, drawing the public's attention away from the level of government that more directly affects them. With the public drawn in, it is more economically appropriate for companies to shift their funding and coverage away from the state legislators. This trickles down to local media stations who can not afford to fund full-time positions meant to cover state-level affairs. Without these staff members, it has become increasingly difficult to stay up-to-date with the state legislatures.

Legally, the state legislatures must provide the public with information about legislators, committees, and their hearings. However, this information is hard to obtain, and, is in formats that are difficult to investigate. For example, in California, the state legislature provides videos of the committee hearings, but the transcriptions

of committee hearings were not required until recently. Even for an active and engaged citizen, there are hundreds of bills with multiple hearings and versions. It is difficult and time consuming to go through days worth of video on one bill, just to find a small segment of a committee hearing they are interested in. Without local reporters, there is no one to summarize the hearings, drastically decreasing the legislature’s transparency, and ultimately dampening the public’s ability to influence the legislative process. By making it difficult for citizens to get involved, the legislative process has evolved into a negotiation between legislators and special interest groups. These special interest groups can make selfish stances on bills without fear of public backlash.

To address this issue, the Digital Democracy project was created¹. Digital Democracy provides a fully indexed and searchable database filled with information about California, New York, Florida, and Texas state legislatures. This information includes fully transcribed and searchable hearing videos, the position of organizations on bills, donations to legislators, voting records, and more.

The screenshot shows the Digital Democracy website interface. At the top, there is a search bar with the text "Search for Bills, Hearings, Speakers, Committees, Organizations" and a magnifying glass icon. Below the search bar are navigation tabs: HEARINGS, BILLS, COMMITTEES, SPEAKERS, and ORGANIZATIONS. The main content area features a profile for Lorena Gonzalez Fletcher, a Democrat from District 80. The profile includes a photo, contact information (Room Number: 2114, Phone: (916) 319-2080, Email: Lorena.Gonzalez.Fletcher@LorenaSGonzalez), and a map of San Diego showing the district. To the right of the profile is a search bar for the speaker's statements and a table of top contributions. The table lists contributions from 2017-2018, 2015-2016, 2013-2014, and 2011-2012, with a total of \$8,800 from Blue Shield of California and \$8,000 from Motor Vehicle Software Corporation.

Contributed from	Total
Blue Shield of California	\$8,800
Motor Vehicle Software Corporation	\$8,000
San Manuel Band of Mission Indians	\$4,400
Faculty For Our Univ. Future, A Comm. Sponsored by the CA Faculty Assn.-SCC	\$4,400

Figure 1.1: The Digital Democracy project’s legislator web page.

¹www.digitaldemocracy.org

**AUGUST 31, 2016 | SENATE STANDING COMMITTEE ON BUSINESS,
PROFESSIONS AND ECONOMIC DEVELOPMENT**

That the Assembly amendments be concurred in

Ayes: 9 Noes: 0 Abstain: 0

Aye Votes

Bates, P.	Gaines, T.	Hernandez, E.	Jackson, H.	Wieckowski,
Block, M.	Galgiani, C.	Hill, J.	Mendoza, T.	B.

AUGUST 31, 2016 | SENATE FLOOR

W/O REF. TO FILE SB465 Hill

Ayes: 38 Noes: 0 Abstain: 1

Abstain/Absent Votes

Moorlach, J.

Aye Votes

Allen, B.	De Leon, K.	Hernandez, E.	Leno, M.	Morrell, M.	Vidak, A.
<u>Anderson, J.</u>	Fuller, J.	Hertzberg, R.	Leyva, C.	Nguyen, J.	Wieckowski,
Bates, P.	Gaines, T.	Hill, J.	Liu, C.	Nielsen, J.	B.
Beall, J.	Galgiani, C.	Hueso, B.	McGuire, M.	Pan, R.	Wolk, L.
Berryhill, T.	Glazer, S.	Huff, B.	Mendoza, T.	Pavley, F.	
Block, M.	Hall, I.	Jackson, H.	Mitchell, H.	Roth, R.	
Cannella, A.	Hancock, L.	Lara, R.	Monning, B.	Stone, J.	

Figure 1.2: The Digital Democracy project’s voting data.

While Digital Democracy provides a plethora of resources to track and monitor state level legislatures, it is still difficult to predict how active and involved a legislator will be during a given bill’s life cycle. By solely looking at key artifacts, such as the legislator’s final vote, it is still difficult to determine how active a legislator was during the bills life cycle. Our goal is to analyze data from the 2015-2016 California State Legislature so that we can summarize and quantify a legislator’s activity across all bills.

Formally, this thesis provides a novel method for summarizing a legislature’s level of activity for a given bill. This summary is represented by an embedding created from a custom neural network called Democracy2Vec. After performing a case study on the 2015-2016 California State Legislature, we were able to validate that our legislators were clustering into 8 distinct groups. These groups can summarize how

legislators will likely act over a session and on a specific bill. Going forward, these embeddings can be used for further research similarly to how word embeddings are used.

This thesis provides the following contributions. First, we created a dataset with over 1200 features related to a legislator’s activity on bills. This dataset was created for the 2015-2016 and 2017-2018 California State Legislature session, the 2017-2018 Florida State Legislature session, and the 2015-2016 New York State Legislature session. These datasets have been provided to the Digital Democracy Research platform. Second, we created a novel neural network called Democracy2Vec and were able to extract embeddings related to legislator activity. These embeddings will also be provided to the Digital Democracy Research platform for further research. Third, we conducted a case study which verifies that the embeddings are meaningful and accurately represent the legislators.

The rest of this document is structured as follows. In Chapters 2 and 3, we go over background information and related work including information about neural networks, embeddings, and research using the Digital Democracy database. Chapter 4 discusses how we extracted data from the Digital Democracy database and how we engineered over 1200 new features. After this we explain our custom neural network, Democracy2Vec, in Chapter 5. Specifically, we discuss how we filtered our data and the structure of the Democracy2Vec model. Next, in Chapter 6, we discuss a case study conducted using the data created from the 2015-2016 California State Legislature. Chapter 7 describes the results of our case study. Finally, Chapter 8 goes over future work.

Chapter 2

BACKGROUND

2.1 California State Legislative Process

Figure 2.1: California bill life cycle [2].

The California state legislature is broken down into two chambers, the Senate and Assembly. Both of these chambers introduce hundreds of bills each year. The legislative process is both a long and complex system that is increasingly opaque. This is especially evident during a bill's life cycle. When a legislator has an idea for a bill, the legislator sends the bill to the legislative counsel to be drafted. After the bill is drafted, the bill is introduced to either the Senate or Assembly, depending on the chamber of the author and can not be acted upon for 30 days after it has been

introduced. Once the bill has been introduced, it is sent to the Rules Committee in the author's chamber; the Rules Committee then sends the bill to committees that delegate over related policy, funding, or ethics. Each committee schedules a hearing to discuss and vote on the bill. Members can vote to pass the bill, pass an amended version of the bill, or defeat the bill by a majority vote. If the bill was passed, it is read for a second time to the floor committee of the authors chamber and assigned a third reading. For the third reading, the author explains the bill and members of the floor perform a roll call vote to pass or defeat the bill. If the bill is defeated, the author can appeal the vote for reconsideration. If the bill passes, the entire process is repeated in the opposite chamber. If the bill passes in the opposite chamber but is amended, the bills differences are resolved with a joint conference committee hearing if the amendments are not initially accepted by the original chamber. If both chambers pass the bill, the bill is sent to the Governor where they can either sign the bill into law or veto it. If the bill is vetoed by the Governor, both houses can overrule it with a two-thirds majority vote.[12]

2.2 Digital Democracy

As evident in Figure 2.1, the legislative process for creating new legislation is fairly elaborate. During this process, most of a legislator's activity happens during committee hearings. These committee hearings not only have legislators but many citizen and lobbyists speaking for or against a bill. All of these hearings are legally required to be filmed and thus provide a public record of a legislator's stance and passion on a bill. While these videos are publicly available, the state legislature has made it difficult to find and view these videos. Citizens, reporters, or lobbyists would have to comb through hundreds of hours of video to find a specific hearing and section where the legislator of interest is speaking on the desired bill. This problem is exacerbated by recent cuts to funding for full time state legislature reports. As international news

corporations focus more on the drama and gridlock of the national government, the public has had less interest in the state legislatures. Because of this, the local media stations can not afford to have full time state legislature reporters. Without these reporters, there is no one to summarize what is happening in state governments. To counter this, the Digital Democracy project was started in 2015 by the Institute of Advanced Technology and Public Policy at the California Polytechnic State University, San Luis Obispo.

Digital Democracy aims to make the state legislatures of California, New York, Texas, and Florida more transparent[3]. To do this, Digital Democracy aggregates hundreds of gigabytes of data related to these legislatures. For California, all committee hearing videos during a session year are downloaded and upscaled through a transcription process. This transcription process involves adding captions to each of the videos while labeling who is speaking and on what bill.

Assembly Budget Subcommittee No. 1 on Health and Human Services Hearing of 05-16-2018

31:27

⌂ f t in

Transcript

Joaquin Arambula	Good morning. This will begin today's sub. one hearing on May 16th. We will begin with issue one.
Joaquin Arambula	When you're ready.
Unidentified Speaker	Okay, do you want to start or? Go ahead, or I can, it's up to you.

+ Agendized Bills
Show

- Hearing Speakers
Hide

Abouhassan, Evelyn	Jordean, Barry
Ader, Mary	Keeslar, Karen
Allen, Chaz	Kent, Jennifer
Alonzo-Diaz, Lupe	Kniffen, Susanna
Arambula, Joaquin	Lindsey, Jordan
Backus, Glen	Manriquez, Guadalupe
Bargmann, Nancy	Mark, Karen
Beckley, Mark	Mecca, Frank
Bellow, Jenny	Millendez, Ryan
Brooks, Sarah	Morales, Monica
Brooks, Kelly	Morales, Lourdes
Carvacha, Rosanna	Mossberg, Kathy
Cervenka, Peter	Mossburg, Kathleen
Cervinka, Pete	Mossburg, Kathy
Chen, Kimberly	Nguy, Linda
Chernenko, Pete	Obernolte, Jay
Child, Curt	Petek, Sonja
Child, Curtis L.	Peterson, Jonathan
Child, Kurt	Pettick, Sonia
Clendenin, Stephanie	Pittman, Brianna
Cook, Chris	Pryor, Selena
Cook, Kris	Rollins, Rick
Dougherty, Brian	Rubio, Blanca
Doyle, John	Schwartz, Angie
Ewing, Toby	Secretary, Committee
Freitas-Norman,	Sever, Will
Lindsey	Shane, Andrew
Gaffney, Leslie	Shilton, Adrienne

Figure 2.2: Digital Democracy committee hearing with transcription.

Additionally, Digital Democracy collects more traditional data on legislators and bills. For a legislator, the project collects the legislator's party, chamber, district, committee membership, voting activity on each bill, and more. For each bill, the Digital Democracy collects data such as who the author is, who sponsors the bill and the changes to the bill content.. A full list of this data can be found in the appendix. All of this data is available for free to the public in a searchable database. This make Digital Democracy an indispensable tool for journalists reporting on the state governments and activists pushing for change at the state level.

2.3 Neural Networks

In this thesis, we use neural networks to classify data. Given a set of inputs and output classes, a neural network can learn a functional relationships between these sets of variables and predict which class the inputs belongs to. For example, given medical measurements of a tumor, a neural network could predict whether the tumor was benign or malignant. When trained, a neural network can learn the function between the inputs and expected output or class.

When broken down, a neural network has unique three components: neurons, weights, and layers. Neurons represent a series of transformation operations and are usually depicted as circles. The weights are paths or connections between neurons represented by a value and an arrow. Finally, layers are groups of neurons, depicted as a line of neurons or circles. A neural network has different types of layers: one input layer, one to many hidden layer(s), and one output layer. These layers are connected through matrices of weights that are randomly initialized. An example of a neural network can be seen in Figure 2.3.

Figure 2.3: Digital Democracy committee hearing with transcription.

The layers are comprised of several neurons. The neurons in the input layer represent the input features for the given data set and no operations are performed. For each neuron in the hidden layer, the following series of transformation operations occur.

$$Y_i = \varphi(\sum X_i W_i) \quad (2.1)$$

For each neuron, the output values of the previous layer are multiplied by their weights, summed, then passed through a function φ called an activation function.

Figure 2.4: A single neuron.

The activation functions limit the output of a neuron to a specific range depending on the function. An example is the sigmoid formula which limits output from 0 to 1. These operations are performed for each neuron in a hidden layer and then repeated for each hidden layer. Generally, each neuron in the hidden layer(s) are connected to every neuron in the next layer. In Figure 2.4, we show what occurs at the neuron level. For the output layer, the same operations are performed, but the activation function is optional.

For a neural network to learn non-obvious relationships, it must be trained with a lot of data. Training is broken down into two steps: forward propagation and backward propagation. For forward propagation, inputs X_1 to X_n are passed through each hidden layer and an output is calculated. Once an output is computed, back propagation starts by calculating a loss between the output and a ground truth. The loss is used to adjust weights throughout the network. This is done by taking the partial derivatives with respect to the weights using the chain rule. By adjusting

the weights, the network is learning about the importance of each feature and can get a value closer to the ground truth.

2.4 Word2Vec

Our custom neural network architecture was inspired by Google's Word2Vec. In this paper, Mikolov et al.[28] created two shallow neural network architectures: Skip-Gram and Continuous Bag of Words (CBOW). The goal of a Skip-Gram model is given a single word, predict the two words before the input word and two words after.

Figure 2.5: Skip-Gram model.

The goal of a Continuous Bag of Words model is to predict a word given the context in a sentence. The context for a CBOW model is the two words prior the target word and two words after.

Figure 2.6: CBOW model.

For this thesis, we focused on the CBOW model. The input layer for the CBOW model is a sparse one hot encoded vector. This vector is of size N , where N is the number of words in their vocabulary and each input neuron represents a single word. The hidden layer is of size P and ranges between 50-300 neurons. The output layer is identical to the input layer but the output of each neuron is the probability that the word is the target word. The most important part of this network are the embeddings. These embeddings are extracted from the hidden layer by multiplying the output of the neurons by their weights. The embeddings are valuable because they can transform a sparse dataset into a more dense dataset with significantly fewer features. While both the Skipgram and CBOW models were unable to consistently predict the target or context words, Mikolov et al. found the embeddings captured relationships and similarities between words and it allowed them to represent words as continuous vectors. From these embeddings, they found that similar words were grouped together and similar relationships between words were represented in the same way, such as the distances between gender specific terms. For example, given

the vector for “king”, if you were to subtract the vector “man” and add the vector “woman”, it would be almost equivalent to the vector “queen”.

2.5 Principal Component Analysis

Figure 2.7: Example of PCA reducing 3 dimensions to 2 dimension.

Principal component analysis (PCA)[18] is a way of summarizing high dimensional data in lower dimensions. When given a set of attributes that describe a data set, some of the features may be redundant while some features may accurately describe the differences over all of the observations. PCA creates new features for the data, projected in a N lower dimension. The new features are created from a mathematical combination of N features which are responsible for the highest variance over all observations.

2.6 Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a way of automatically finding topics within a corpus of documents. LDA is able to do this in four steps. First, a number of topics is selected, N. Second, each word is randomly assigned a topic. Third, for each word, LDA looks at the word’s occurrence in the topic and the number of topics in the document and updates the topic based on the probability that the word is in the given topic. Finally, each document is assigned a mixture of topics based on the ratio

of topics assigned to each word. For example, a document could be 30% topic 1 and 70% topic 2. In this thesis, we used LDA to assign a single topic to each bill. The topic that was selected was the topic with the highest percent.

2.7 Software Packages

In this thesis, we used several python packages during our data extraction process. The following section will describe these packages and why we chose to use them.

2.7.1 Pandas

All the extraction, transfer, and load processes were handled using the software package Pandas[13]. Pandas allows us to perform all formatting operations on the data in code rather than in MySQL. We found that it was substantially faster to perform unstructured queries and format them with Pandas than formatting the data using more complex MySQL queries.

2.7.2 TextBlob

To extract features such as the number of words, nouns and adjectives, we used the TextBlob text processing package[16], which can identify each word’s part of speech. While TextBlob can also provide a sentiment score, we found that the Vader sentiment package provided better results.

2.7.3 Vader Sentiment

We used Vader, a sentiment analysis tool that specializes in short, to analyze the sentiment of a legislators speech[17]. We found that Vader was able to sufficiently analyze our legislator utterances.

Chapter 3

RELATED WORK

Predicting a state legislator’s level of activity or participation in a bill’s life-cycle based on an incoming bill and a legislator’s previous history has not been attempted before. Kraft et al. created a model that predicted roll call votes from bill text[26]. Their model achieved an average of 90.7% accuracy. In the first paper, Kraft et al. built a model based on the federal legislature while ours is focused on the California state legislature. Kraft et al.’s model only focused on bills that were passed through a roll call vote while we used every committee vote and floor vote to build our model. Similarly, Kornilova et al. carried out a research study on roll-call vote using data over several sessions. Their model was able to incorporate metadata about a legislators ideologies over time [25]. This paper shows a 4% improvement over existing methods by incorporating embeddings into their system. In both Kornilov et al. and Kraft et al.’s experiments, the only legislator behavioral meta-data was political ideology. In our experiments, we show that using a combination of bill data and legislator behavioral meta-data to create embeddings has promise. Furthermore, our study is a first of its kind analysis since it focuses on state legislatures. Another study done by Iyyer et al., uses word embeddings and recursive neural networks to identify political ideologies in text [23]. The results in this study show the authors were able to outperform existing methods. In this study, the authors use word embeddings as input into their model as oppose to our goal of creating new embeddings. In a cross sectional study, Cohen et al. [20] created *a priori* factor model to identify a legislator’s support of the tobacco industry in Canada. Cohen et al.’s work was based in Canada and only focused on identifying legislator support toward bills related to the tobacco industry.

Because of the success from Word2Vec, many different projects have used it’s model as an inspiration for a model of their own. For example, Quoc V. Le and

Tomas Mikolov wrote a paper called Distributed Representations of Sentences and Documents [27], commonly known as Doc2Vec. In this paper, Mikolov et al. introduce Paragraph Vectors. These vectors are able to represent documents in a dense feature space. To do this, Mikolov et al. trained a model to predict missing words within the document. The authors' goal was to capture ordering and semantic meaning of words within sentences.

Another project which stemmed from Word2Vec is Node2Vec: Scalable Feature Learning for Networks [22]. Researchers, Aditya Grover and Jure Leskovec, had a goal of learning feature representations of nodes in networks. To do this, Node2Vec tries to maximize the likelihood of preserving network neighborhoods. From this, Node2Vec is able to represent network nodes in a low dimensional feature space.

The last Word2Vec project we will mention is Location2Vec [31]. In Location2Vec: Generating Distributed Representation of Location by Using Geo-tagged Microblog Posts, Shoji et al. attempt to represent a location in a low dimensional feature space using microblogs. Using a shallow neural network, Shoji et al. tried to predict missing words from microblogs, such as tweets. While Doc2Vec, Node2Vec, and Location2Vec draw inspiration from Word2Vec, their domains are completely different from our system.

As previously mentioned, Digital Democracy has an extremely rich data set that has been applied to a variety of research problems. In an earlier thesis, Andrew Wang developed the TONGS (TLDR; Opinion Network Guide System) library for conducting sentiment analysis[33]. This library uses TensorFlow's Word2Vec to convert words into a vector space representation. This library showed significant improvements over traditional sentiment analysis libraries by looking at a variety of different descriptive data sources related to the legislator. While this thesis uses sentiment analysis, our sentiment feature does not heavily depend on precise measurements of sentiment.

Christopher Wu's thesis, Sentiment Knowledge Extraction With Entity Recog-

nition (SKEWER), is another work built around Digital Democracy[34] that extends the capabilities of TONGS. SKEWER is a pipeline for extracting sentiment and entities from a given text. Wu found that SKEWER is extremely proficient at recognizing entities within a person’s speech. Specifically, it extracts lobbyists, organizations, and a speaker’s identity during committee meetings. Our work uses legislators’ speech as a feature; their identities were known throughout the process.

In September of 2017, Daniel Kauffman built a system that used a legislator’s utterance to determine their alignment toward a known entity[24]. This allowed users to predict a legislator’s alignment with specific organizations with know views. While we do use utterance data in this thesis, we do not look at external organization. Additionally, this research does not use the Digital Democracy project’s alignment data.

In March of 2018, Aditya Budhwar tried to predict a legislators vote by examining their speech prior to a vote[19]. In this thesis, we also analyzed a legislator speech prior to voting using a less in-depth methodology. While we used similar methods to [19], the objective of our work is completely different. For the scope of this thesis, we needed to analyze whether or not the legislator had a non-neutral sentiment and collected features about the amount of time a legislator spent speaking on a bill. The objective of [19] was to predict a legislator’s vote completely dependent on only features related to a legislator’s speech.

THE LEGISLATOR’S ACTIVITY ON BILLS (LAB) DATASET

4.1 The Digital Democracy Project Database Overview

All of the data for this thesis was provided by the Digital Democracy project. The Digital Democracy project’s database (DDDB) aggregates several different data sources into one database. These data sources include FollowTheMoney[4], LegInfo[9], Maplight[10], and OpenStates [11]. The data is then used to power the Digital Democracy project’s website and research platform. A few examples of data that is stored in the DDDB are: a legislators name, party affiliation, and district, all information about committee memberships, the full text and voting records of each bill, and full transcriptions of every utterance said during a committee hearing along with the speaker information.

4.2 Extraction Methods

For this thesis, we extracted all of our features from the California State Legislature 2015-2016 session in the DDDB. We extracted as many features as possible that accurately and uniquely describe a legislator, a bill, and a legislator’s activity on a bill. To do this, we would executed generic queries with relative few filters through a Python client. After reading the result into a Pandas DataFrame, we would extracted existing features or create a new features from the DataFrame. For example, if we extracted the user ID, the start time stamp of an utterance, and the end time stamp of an utterance, we could subtract the end time stamp from the start time stamp then aggregate our result per user to get the total time a user spoke. Overall, our features are sorted into three categories: legislator, bill, and a legislator’s activity on a bill.

4.3 Legislator Features

For each legislator, our goal was to find static features that uniquely summarized the legislator over an entire session. This includes features such as the legislators party and the number of committees they were a member of. Table 4.1 presents the full list of legislator features.

Attribute	Description	Data Type	Feature Shape
Party	The party of the legislator: Democrat or Republican.	One-hot encoded vectors.	120 x 2
House	The house where the legislator resides: Assembly or Senate.	One-hot encoded vectors.	120 x 2
District	The Assembly or Senate district number.	One-hot encoded vectors (120 values).	120 x 2
Total Bill Discussions	The number of bill discussions a legislator attended.	Numeric.	120 x 1
Total Bill Discussion by Topic	The number of bill discussions a legislator attended split by the topic of a bill.	Numeric.	120 x 30
Average Utterance Time	The average time a legislator speaks per utterance.	Numeric in seconds.	120 x 1
Total Speaking Time	The total time a legislator spent speaking on bills.	Numeric in seconds.	120 x 1
Total Authorships	The number of times a legislator authored a bill.	Numeric.	120 x 1

Committee Membership: Member	The number of committees a legislator served on as a member.	Numeric.	120 x 1
Committee Membership: Co-Chair	The number of committees a legislator served on as a co-chair.	Numeric.	120 x 1
Committee Membership: Vice-Chair	The number of committees a legislator served on as a vice-chair.	Numeric.	120 x 1
Committee Membership: Chair	The number of committees a legislator served on as the committee chair.	Numeric.	120 x 1
Total Ayes	The total number of times a legislator voted aye during the entire session.	Numeric.	120 x 1
Total Noes	The total number of times a legislator voted noe during the entire session.	Numeric.	120 x 1
Total ABS	The total number of times a legislator abstained from voting during the entire session.	Numeric.	120 x 1
Total Votes	The total number of times a legislator voted on a bill during the entire session.	Numeric.	120 x 1
Average Bill Discussion Time	The average time a legislator spent speaking during a bill discussion.	Numeric in seconds.	120 x 1
Committee Membership	Which committees a legislator serves on.	A single one-hot encoded vector per committee.	120 x 71

Voted with Party	The number of times a legislator voted with the majority of their party.	Numeric.	120 x 1
Total votes against party	The number of times a legislator voted against the majority of their party.	Numeric.	120 x 1
Total Bill Discussions as Committee Member	The number of bill discussions a legislator attended as a committee member.	Numeric.	120 x 1
Total Bill Discussions not as Committee Member	The number of bill discussions a legislator attended not as a committee member.	Numeric.	120 x 1
Total Bill Discussion as Bill Sponsor	The number of bill discussions a legislator attended as a sponsor.	Numeric.	120 x 1
Total Bill Discussion not as Bill Sponsor	The number of bill discussions a legislator attended not as a sponsor.	Numeric.	120 x 1
Total Utterances	The number of utterances a legislator had over the entire session.	Numeric.	120 x 1
Total Utterances as a Committee Member	The number of utterances a legislator had over the entire session as a committee member.	Numeric.	120 x 1
Total Utterances not as a Committee Member	The number of utterances a legislator had over the entire session not as a committee member.	Numeric.	120 x 1

Average Bill Discussion Time based on bill result	The average time a legislator spent speaking on bills that passed/failed.	Numeric.	120 x 2
Average Bill Discussion Time based on bill topic	The average time a legislator spent speaking on bills per topic.	Numeric.	120 x 30

Table 4.1: Legislator Features

4.4 Bill Features

The bill features contain information that describes the contents of the bill and the status of the bill as it passed through its life cycle. Some features include the topic of the bill, the number of bill versions, and summary information about the voting. These bill features were independent of the legislators and can not be correlated with any of them.

Attribute	Description	Data Type	Feature Shape
Chamber Origin	The chamber where the bill originated from: Assembly, Senate, or Joint.	One-hot encoded vector.	686 x 3
Bill Status	The final status of the bill.	One-hot encoded.	686 x 8
Assembly Hearings	The number of assembly committee hearings.	Numeric.	686 x 1
Senate Hearings	The number of senate committee hearings.	Numeric.	686 x 1

Joint Hearings	The number of joint committee hearings.	Numeric.	686 x 1
Abstain: Democrat	The number of Democratic legislators that abstained from voting on the bill.	Numeric.	686 x 1
Abstain: Republican	The number of Republican legislators that abstained from voting on the bill.	Numeric.	686 x 1
Aye: Democrat	The number of Democrat legislators that voted Aye on the bill.	Numeric.	686 x 1
Aye: Republican	The number of Republican legislators that voted Aye on the bill.	Numeric.	686 x 1
Noe: Democrat	The number of Democrat legislators that voted Aye on the bill.	Numeric.	686 x 1
Noe: Republican	The number of Republican legislators that voted Aye on the bill.	Numeric.	686 x 1
Topic	The topic of the bill text.	One-hot encoded.	686 x 30
Total Ayes	The total number of aye votes on the bill.	Numeric.	686 x 1
Total Noes	The total number of noe votes on the bill.	Numeric.	686 x 1
Total ABS	The total number of legislator that abstained from voting on the bill.	Numeric.	686 x 1
Number of words	The total number of words on the final version of the bill.	Numeric.	686 x 1
Number of versions	The number of version the bill went through.	Numeric.	686 x 1
Number of bills passed per topic	The number of bills that passed (Chapter or Enrolled) per topic	A Numeric per topic.	686 x 30

Number of bills failed per topic	The number of bills that failed (Neither Chaptered nor Enrolled) per topic	A Numeric per topic.	686 x 30
Number of bills passed per committee	The number of bills that passed per committee.	A Numeric per committee.	686 x 71
Number of bills failed per committee	The number of bills that failed per committee.	A Numeric per committee.	686 x 71
Number of utterances per topic	The total number of utterances per topic.	A Numeric per topic.	686 x 30
Number of utterances per topic passed.	The total number of utterances per topic for bills that passed.	A Numeric per topic.	686 x 30
Number of utterances per topic failed	The total number of utterances per topic for bills that failed.	A Numeric per topic.	686 x 30
Number of bill discussions per topic	The total number of bill discussions per topic.	A Numeric per topic.	686 x 30
Number of bill discussions per topic passed.	The total number of bill discussions per topic for bills that passed.	A Numeric per topic.	686 x 30
Number of bill discussions per topic failed	The total number of bill discussions per topic for bills that failed.	A Numeric per topic.	686 x 30

Number of committee hearings per topic	The total number of committee hearings per topic.	A Numeric per topic.	686 x 30
Number of committee hearings per topic passed.	The total number of committee hearings per topic for bills that passed.	A Numeric per topic.	686 x 30
Number of committee hearings per topic failed	The total number of committee hearings per topic for bills that failed.	A Numeric per topic.	686 x 30
Aye votes per topic	The number of aye votes per topic	A Numeric per topic.	686 x 30
Noe votes per topic	The number of noe votes per topic	A Numeric per topic.	686 x 30
Abstain votes per topic	The number of legislators that abstained from voting per topic.	A Numeric per topic.	686 x 30
Mean Aye votes per topic	The mean number of aye votes per topic	A Numeric per topic.	686 x 30
Mean Noe votes per topic	The mean number of noe votes per topic	A Numeric per topic.	686 x 30
Mean Abstain votes per topic	The mean number of legislators that abstained from voting per topic.	A Numeric per topic.	686 x 30
Total time spent talking on each topic passed bills	The total amount of time spent talking on bills that passed.	A Numeric per topic.	686 x 30

Total time spent talking on each topic failed bills	The total amount of time spent talking on bills that failed.	A Numeric per topic.	686 x 30
Average time spent talking on each topic passed bills	The average amount of time spent talking on bills that passed.	A Numeric per topic.	686 x 30
Average time spent talking on each topic failed bills	The average amount of time spent talking on bills that failed.	A Numeric per topic.	686 x 30

Table 4.2: Bill Features

4.5 Activity Features

The activity feature set includes any action or description of an action a legislator can perform on a bill. This means that for each bill, we have an observation for each legislator. These activity features include whether or not the legislator was the author of the bill and how long the legislator spoke on a bill.

Attribute	Description	Data Type	Feature Shape
Author	Whether or not the legislator was the author of the bill.	One-hot encoded vector.	83006 x 2
Shared Chamber	The bill originates in the same house as the author.	One-hot encoded vector.	83006 x 2

Utterances	The number of utterances a legislator spoke on a bill.	Numeric.	83006 x 1
Utterances as a Committee Member	The number of utterances a legislator spoke on a bill as a committee member.	Numeric.	83006 x 1
Utterances not as Committee Member	The number of utterances a legislator spoke on a bill not as a committee member.	Numeric.	83006 x 1
Number of Words	The number of words a legislator spoke on a bill.	Numeric.	83006 x 1
Number of nouns	The number of nouns a legislator spoke on a bill.	Numeric.	83006 x 1
Number of verbs	The number of verbs a legislator spoke on a bill.	Numeric.	83006 x 1
Number of adjectives	The number of adjectives a legislator spoke on a bill.	Numeric.	83006 x 1
Average Polarity	The average polarity score of a legislators utterances.	Numeric.	83006 x 1
Average Subjectivity	The average subjectivity score of a legislators utterances.	Numeric.	83006 x 1
Overall Polarity	The overall polarity score of a legislators utterances.	Numeric.	83006 x 1
Overall Subjectivity	The overall subjectivity score of a legislators utterances.	Numeric.	83006 x 1
Percent Voted Aye	The proportion of votes a legislator voted aye.	Numeric.	83006 x 1

Notes	The number of times a legislator voted on a bill.	Numeric.	83006 x 1
Bill Discussions	The number of bills discussions a legislator attended for a bill.	Numeric.	83006 x 1
Voted with Party	Whether or not a legislator voted with the majority of their party.	One-hot encoded vector.	83006 x 2
Speaking Time	Total time spent speaking on a bill.	Numeric in seconds.	83006 x 1
Average Utterance Time	The average length of a legislator's utterances on a bill.	Numeric in seconds.	83006 x 1
Average Bill Discussion Time	The average time a legislator spent speaking at each bill discussion for a bill.	Numeric in seconds.	83006 x 1

Table 4.3: Participation Features

Chapter 5

DEMOCRACY2VEC

This chapter describes our custom model and techniques we used to filter our training data. We propose Democracy2Vec, a novel neural network implementation that draws inspiration from Googles Word2Vec. The objective of our network is to create embeddings that represent how active a legislator will be during a bill’s life cycle and how they will likely act on that bill.

5.1 Data Filtering

While building this network, we found that there were several factors that made our data set unbalanced. This section describes these factor and how we attempted to balance our data set with filtering techniques.

5.1.1 Voting Percentage

Within both chambers of the California State Legislature, there are 42 Republicans and 78 Democrats. The Assembly is comprised of 52 Democrats and 28 Republicans, while the Senate has 26 Democrats and 14 Republicans. In both chambers, Democrats control 65% of the seats which means they can push legislation through when the legislators vote along party lines. We found that there is less legislator activity on bills that followed party lines. Additionally, the legislative body passes a lot of bills with a unanimous vote. These bills are not controversial, and therefore there is little to no debate on them. Because of these factors, we required that all bills in our training set have less than 70% voter agreement. To do this, we take the max between the total number of aye, abstain, and noe votes, divide by the total votes and check if that proportion is less than 70%. This requirement allowed us to look at bills with higher legislative activity where legislators broke party lines.

5.1.2 Unique Voters

During the session year, there are a lot of bills that die before leaving their committee(s). These bills cause our voting attributes to become sparse. To reduce the sparse data, we filtered out bills that did not have at least 60 unique voters, which guarantees the bill has been voted on by at least half of the legislative body.

5.1.3 Feature Reduction

During our training process, we found that a lot of our features had a negative effect on our embeddings and/or accuracy measurements. The reason some these features had such an affect was that our network was extremely shallow and we had very few observations. Due to these factors, it is difficult for our network to learn and incorporate complicated features (i.e., features split by topic). We found that the remaining features accurately and uniquely describe legislators, bills, and legislator activity. Table 5.1 describes the feature set used in our final model.

Attribute	Type
Total Authorships	Legislator
Party	Legislator
Chamber	Legislator
Number of Committee Positions	Legislator
Bill Chamber Origin	Bill
Bill Status	Bill
Number of Bill Hearings	Bill
Number of Bill Hearings per Chamber	Bill
Votes Broken Down by Party	Bill
Overall Votes	Bill
Bill Topic	Bill

Number of Bill Discussions	Bill
Average Utterance Length for a Bill	Bill
Sponsorship Type	Bill
Number of Utterances as Committee Member	Bill
Number of Utterances not as Committee Member	Bill
Overall Sentiment	Activity
Average Sentiment	Activity
The number of utterances said on a bill	Activity
The number of words said on a bill	Activity
The average number of words said during utterances	Activity
Total time spent speaking on a bill	Activity
The number of times a legislator voted aye	Activity
The number of nouns, adjectives, and verbs said by a legislator	Activity
Broke party lines on vote	Activity
Average time spent speaking during bill discussions	Activity
Is the legislator the Author	Activity
Do the legislator and bill share the chamber of origin	Activity
The number of votes a legislator took	Activity

Table 5.1: Final Feature Set

5.2 Network Motivation

As stated above, this network draws inspiration from Googles Word2Vec network. Our original idea for this network was given a set of input's from our legislator and bill features, predict a feature from our activity features. This allows us to predict on new incoming bills where the activity features are missing. After creating this

network, we found that the embeddings were not meaningful and did not describe any relationships in our data. The issue for was that most of our features are static. Given that there are only 121 legislators and roughly 700 unique bills, there is not enough variability across our observations. Given that most of the variability in our data is in the activity features, we need to include them in our training. The issue this causes is that we can not predict on new incoming bills if the activity features are used for both training and predicting. Formally, this means our network has two requirements; we called these requirements our training requirement and our prediction requirement. The training requirement is that we need to use some of our activity features during the training process to add the necessary variability to our data. The prediction requirement is that we need to be able to predict using just the legislator and bill features so that we can predict on new incoming bills. From these requirements, we built Democracy2Vec to tackle our goal. This section describes the structure of our model in detail which can be seen in Figure 5.1. Our model has three unique layers: the single embedding layer, the multiple embedding layer, and the output layer.

Figure 5.1: Democracy2Vec model, amount of neurons and weights not to scale.

5.3 Single Embedding Section

The first layer of our network creates a reduced embedding representations of each of our feature types: legislator, bill, and activity. Each data type embedding has fewer neurons than the original input feature set. For instance, we have roughly 60 bill features, while our bill single embedding section has 12 neurons. This single embedding allows us to learn important features and reduce the dimensionality of our feature space independent from other features.

5.4 Multiple Embedding Section

Using the single embeddings from the previous section, we created four new vectors. Three of these vectors are dual embeddings, as they are created by concatenating two single embeddings: legislator/bill, bill/activity, and legislator/activity. The fourth vector is referred to as a global embedding, where all three single embeddings concatenated into one vector. We then create a reduced embedding representation of all four vectors of a chosen size, 10 neurons. By standardizing the size of the multiple embeddings, we have an equal number of neurons being used to calculate an output.

5.5 Output Section

Each of the dual embeddings are used to predict values related to the feature type they are missing. The legislator/bill dual embedding predicts activity features - specifically whether the legislator is a sponsor of the bill, if the legislator spoke on the bill, and if legislator had a non-zero sentiment score. This is a multi-label output and these values are predicted separate from each other. The bill/activity dual embedding helps predict which legislator performed the actions on the bill - this is a legislator feature. The legislator/activity dual embedding is used to predict a bill feature, the bill the legislator was acting on. Finally, the global embedding shares the same output neurons as the dual embedding but is used to predict all of the outputs. A list of these features can be seen in Table 5.2.

Feature Type	Description	Output Type
Legislator	Which legislator performed the actions on the bill.	One-hot encoded vector
Bill	The bill the legislator was acting on.	One-hot encoded vector
Activity	Is the legislator a sponsor of the bill.	Binary
Activity	Did the legislator speak on the bill.	Binary
Activity	Did the legislator have a non-zero sentiment speaking score.	Binary

Table 5.2: Output Features

5.6 Explanation

As stated above, we have two requirements. Our network needs to train with the activity features but predict without them. Our single embedding section, in combination with the multiple embedding section, solve both of these requirements. Each one of our dual embeddings and our global embedding essentially act as their own network, taking in two single embeddings. For example, one dual embedding takes in the legislator single embedding and the bill single embedding while another takes in the bill single embedding and the activity single embedding. It is important to note that the dual embeddings share the same single embeddings as inputs. So, in this example, the bill single embedding is the same for both of the dual embeddings. Since the dual embeddings use the same single embeddings, information that is learned during training from one dual embedding is then back propagated into the single embedding and used in the next epoch for other dual embeddings. This meets our training requirement because we use our activity features to train our network and

learn about legislator activity patterns. Because the single embeddings are created independently and dual embeddings are created independently, we can isolate portions of the network because there are no interconnecting weights. This means that we can use the portion that creates the legislator single embedding, the bill single embedding and the legislator/bill dual embedding then predicts the activity features solving our prediction requirement.

Chapter 6

EXPERIMENTS

The goal of our experiment is to produce meaningful embeddings that allows us to measure a legislator’s passion on a given bill or all bills over an entire session. Note that we are not focused on our prediction accuracy, but rather trying to optimize our network for the legislator/bill dual embedding. We chose this embedding because it predicts three values that represent a legislator’s activity: whether the legislator is a sponsor, whether the legislator spoke, and whether the legislator had a non-zero sentiment score on the bill.

6.1 Training

We split our data into two groups, a training and test set, with 80% of our data in the training set and 20% of our data in the test set. To calculate loss, we used the cross entropy loss function because all of our outputs were classifications. Since we wanted to optimize our network for the legislator/bill dual embedding, we weighed the loss of the activity prediction more. Additionally, the global embeddings contain information about the output, so we weighted the loss from the prediction by global embeddings less. A list of weights is provided in Table 6.1.

Embedding Type	Prediction Data Type	Loss Weight
Dual	Legislator	0.3
Dual	Bill	0.2
Dual	Activity	0.2
Global	Legislator	0.125
Global	Bill	0.125
Global	Activity	0.05

Table 6.1: Loss Weight used in Training.

After training our network for 300 epochs, we found that our network was only able to predict if legislator was sponsor well. In Tables 6.2 and 6.3, we can see the precision, recall and f-score for our training and test set.

Prediction	Measurement	Score
Sponsor	Precision	.791
Sponsor	Recall	0.723
Sponsor	F-score	0.756
Not a Sponsor	Precision	0.978
Not a Sponsor	Recall	0.985
Not a Sponsor	F-score	0.981

Table 6.2: Sponsorship precision, recall, and F-score on our training data set.

Prediction	Measurement	Score
Sponsor	Precision	.789
Sponsor	Recall	0.695
Sponsor	F-score	0.739
Not a Sponsor	Precision	0.977
Not a Sponsor	Recall	0.986
Not a Sponsor	F-score	0.982

Table 6.3: Sponsorship precision, recall, and F-score on our test data set.

6.2 Embeddings

Once our model was sufficiently trained, we predicted on our entire data set and extracted our legislator/bill embeddings. These embeddings were continuous vectors

Figure 6.1: Average embeddings colored by house.

Figure 6.2: Average embeddings colored by party.

of length 10. To visualize and better understand these vectors, we performed PCA. Using the first three principal components, we were able to explain 98% of the variance of our data set. We then averaged the vectors over all bills with these principal component vectors and were able to notice some groupings.

In Figures 6.1 and 6.2 we observed that legislators of similar houses and party are grouped together. Because of this, we took our average embeddings and performed K-Means Clustering on them. Following these observations, we took our average embeddings, performed K-Means Clustering on them, and obtained eight distinct groups of legislators.

Figure 6.3: Embeddings averaged over all bills, colored by K-Means clusters.

Chapter 7

CASE STUDY

7.1 Validation Method

To further investigate the clusters and the relationships within them, we performed a case study. We took our eight clusters to a political expert, Hans Poschman[5], to investigate our results. Mr. Poschman is the program and fellowship director of the Institute of Advanced Technology and Public Policy. He was also a district director for Assemblyman and Senator Sam Blakeslee and has spent his life in California politics. We provided Mr. Poschman with a list of legislators along with basic information such as their party, chamber, and cluster. We asked him to investigate the cluster and determine whether or not the cluster had any significance. Note, the number of the cluster was assigned during K-Means clustering and does not carry any meaning.

7.1.1 Important Senate Democrats Cluster (Cluster 5)

Figure 7.1: Important Senate Democrats Cluster

One of the first clusters our political expert identified was cluster 5. This cluster is comprised of prominent Senate Democrats who were generally chairs of committees. For example, Lois Wolk, the majority whip in the Senate, was part of this group.

Name	District	Chamber	party
Fran Pavley	27	Senate	Democrat
Loni Hancock	9	Senate	Democrat
Richard Pan	6	Senate	Democrat
Bill Monning	17	Senate	Democrat
Lois Wolk	3	Senate	Democrat
Marty Block	39	Senate	Democrat
Jim Beall	15	Senate	Democrat
Mark Leno	11	Senate	Democrat
Holly Mitchell	30	Senate	Democrat
Benjamin Allen	26	Senate	Democrat
Ricardo Lara	33	Senate	Democrat

Table 7.1: Cluster 5 legislators.

7.1.2 Important Senate Republicans Cluster (Cluster 4)

Figure 7.2: Important Senate Republicans Cluster

The second cluster Mr. Poschman identified was cluster 4. This cluster is similar to cluster 5, but for the Senate Republicans. It contains senior Republicans that were vice-chairs and also all of the minority leaders during the session, such as Jean Fuller.

Name	District	Chamber	party
Bob Huff	29	Senate	Republican
Jean Fuller	16	Senate	Republican
Patricia Bates	36	Senate	Republican
Mike Morrell	23	Senate	Republican
Sharon Runner	21	Senate	Republican
Ted Gaines	1	Senate	Republican
Anthony Cannella	12	Senate	Republican
Tom Berryhill	8	Senate	Republican
Andy Vidak	14	Senate	Republican

Table 7.2: Cluster 4 legislators.

7.1.3 Centered Senators Cluster (Cluster 0)

Figure 7.3: Centered Senators Cluster

In cluster 0, we found that a majority of the legislators were Senators. Interestingly, Mr. Poschman identified that this group mainly contained moderate Republicans and Conservative democrats. He also noted that these democrats were considered to be more pro-business rather than pro-union.

Name	District	Chamber	party
Isadore Hall	35	Senate	Democrat
Jeff Stone	28	Senate	Republican
Ben Hueso	40	Senate	Democrat
Tony Mendoza	32	Senate	Democrat
Joel Anderson	38	Senate	Republican
Steve Glazer	7	Senate	Democrat
Carol Liu	25	Senate	Democrat
Janet Nguyen	34	Senate	Republican
Jerry Hill	13	Senate	Democrat

Jim Nielsen	4	Senate	Republican
Mike McGuire	2	Senate	Democrat
Susan Eggman	13	Assembly	Democrat
Robert Hertzberg	18	Senate	Democrat
Hannah-Beth Jackson	19	Senate	Democrat
Kevin De Leon	24	Senate	Democrat
Ed Hernandez	22	Senate	Democrat
Richard Roth	31	Senate	Democrat
John Moorlach	37	Senate	Republican
Cathleen Galgiani	5	Senate	Democrat
Rudy Salas	32	Assembly	Democrat

Table 7.3: Cluster 0 legislators.

7.1.4 Centered Assemblymen Cluster (Cluster 1)

Figure 7.4: Centered Assemblymen Cluster

Cluster 1 was similar to cluster 0 as it also contained moderate Republicans and

conservative Democrats, however cluster 1 contains Assemblymen instead of Senators. An example of this would be Katcho Achadjian.

Name	District	Chamber	party
Chad Mayes	42	Assembly	Republican
Marc Steinorth	40	Assembly	Republican
Beth Gaines	6	Assembly	Republican
William Brough	73	Assembly	Republican
Anthony Rendon	63	Assembly	Democrat
Ken Cooley	8	Assembly	Democrat
Brian Jones	71	Assembly	Republican
David Hadley	66	Assembly	Republican
Joaquin Arambula	31	Assembly	Democrat
Ling Ling Chang	55	Assembly	Republican
Kristin Olsen	12	Assembly	Republican
K.H. "Katcho" Achadjian	35	Assembly	Republican

Table 7.4: Cluster 1 legislators.

7.1.5 Education-Focused Cluster (Cluster 3)

Figure 7.5: Education-Focused Cluster

The most difficult cluster to identify a common theme for was cluster 3. However, Mr. Poschman noticed that these legislators were heavily focused on legislation related to education. Funnily enough, we found that most legislators that resigned during the session were in this cluster as well.

Name	District	Chamber	party
Henry Perea	31	Assembly	Democrat
Shirley Weber	79	Assembly	Democrat
Mike Gipson	64	Assembly	Democrat
Bill Quirk	20	Assembly	Democrat
Bill Dodd	4	Assembly	Democrat
Jim Wood	2	Assembly	Democrat
Sebastian Ridley-Thomas	54	Assembly	Democrat
Cristina Garcia	58	Assembly	Democrat
Tom Daly	69	Assembly	Democrat

Roger Hernandez	48	Assembly	Democrat
Ed Chau	49	Assembly	Democrat
Adam Gray	21	Assembly	Democrat
Ian Calderon	57	Assembly	Democrat
Jimmy Gomez	51	Assembly	Democrat
Susan Bonilla	14	Assembly	Democrat
Miguel Santiago	53	Assembly	Democrat
Reginald Jones-Sawyer	59	Assembly	Democrat
Toni Atkins	78	Assembly	Democrat
Kansen Chu	25	Assembly	Democrat
Mark Stone	29	Assembly	Democrat
Patty Lopez	39	Assembly	Democrat
Cheryl Brown	47	Assembly	Democrat
Eduardo Garcia	56	Assembly	Democrat
Mike Gatto	43	Assembly	Democrat
Evan Low	28	Assembly	Democrat
Bob Wieckowski	10	Senate	Democrat
Luis Alejo	30	Assembly	Democrat
Lorena Gonzalez Fletcher	80	Assembly	Democrat
Marc Levine	10	Assembly	Democrat
Matthew Dababneh	45	Assembly	Democrat
Jose Medina	61	Assembly	Democrat
Jim Frazier	11	Assembly	Democrat

Table 7.5: Cluster 3 legislators.

7.1.6 Democratic Line Breakers Cluster (Cluster 2)

Figure 7.6: Democratic Line Breakers

Poschmann found that the legislators in cluster 2 were known to break party lines. In other words, these legislators were bipartisan and willing to change their vote to make progress. An example of this kind of legislator would be Jim Cooper.

Name	District	Chamber	party
Kevin Mullin	22	Assembly	Democrat
Jacqui Irwin	44	Assembly	Democrat
Freddie Rodriguez	52	Assembly	Democrat
Philip Ting	19	Assembly	Democrat
Chris Holden	41	Assembly	Democrat
Rob Bonta	18	Assembly	Democrat
Das Williams	37	Assembly	Democrat
David Chiu	17	Assembly	Democrat
Tony Thurmond	15	Assembly	Democrat
Patrick O'Donnell	70	Assembly	Democrat

Richard Gordon	24	Assembly	Democrat
Richard Bloom	50	Assembly	Democrat
Jim Cooper	9	Assembly	Democrat
Kevin McCarty	7	Assembly	Democrat
Nora Campos	27	Assembly	Democrat
Adrin Nazarian	46	Assembly	Democrat

Table 7.6: Cluster 2 legislators.

7.1.7 Republicans Line Breaker Cluster (Cluster 7)

Figure 7.7: Republicans Line Breaker Cluster

Cluster 7 was similar to cluster 2, however these legislators were Republicans. Additionally, Pocshmann furthered noted that these legislators are outgoing and outspoken. Breaking party lines involves reaching out to Democratic legislators and negotiating with them. For example, Republican Assemblywoman Shannon Grove is in this cluster.

Name	District	Chamber	party
Scott Wilk	38	Assembly	Republican
Travis Allen	72	Assembly	Republican
Jim Patterson	23	Assembly	Republican
Frank Bigelow	5	Assembly	Republican
Shannon Grove	34	Assembly	Republican
Matthew Harper	74	Assembly	Republican
Young Kim	65	Assembly	Republican
Rocky Chavez	76	Assembly	Republican
Jay Obernolte	33	Assembly	Republican
Tom Lackey	36	Assembly	Republican
Melissa Melendez	67	Assembly	Republican

Table 7.7: Cluster 7 legislators.

7.1.8 Partisan Legislator Cluster (Cluster 6)

Figure 7.8: Partisan Legislators Cluster

Finally, Mr. Poschman labelled cluster 6 as mainly partisan legislators. In other words, these legislators rarely worked with legislators from the opposing party. For example, Republican Assemblyman Brian Dahle represents district 1, which is heavily Republican. Legislators like Dahle satisfy the majority of his votes by not wavering from his party’s base.

Name	District	Chamber	party
James Gallagher	3	Assembly	Republican
Autumn Burke	62	Assembly	Democrat
Marie Waldron	75	Assembly	Republican
Eric Linder	60	Assembly	Republican
Connie Leyva	20	Senate	Democrat
Donald Wagner	68	Assembly	Republican
Brian Dahle	1	Assembly	Republican
Brian Maienschein	77	Assembly	Republican
Catharine Baker	16	Assembly	Republican
Devon Mathis	26	Assembly	Republican

Table 7.8: Cluster 7 legislators.

7.1.9 Misclassifications

While we were able to identify common themes among a majority of the legislators, we acknowledge that the clusters are not perfect. For example, we grouped Anthony Rendon into a cluster of moderate conservatives when he should be part of the partisan cluster 6. Another example of this would be Catherine Baker. While we grouped her into cluster 6, she should be in cluster 1 with our other centered Assemblymen. We attribute these mistakes to the K-Means Clustering algorithm. While investigating these misclassifications, we noticed that the legislator’s 3-D point was always

extremely close to the correct cluster (i.e. Anthony Rendon's 3-D point was very close to cluster 6 and Catherine Baker's point was close to cluster 1).

Chapter 8

CONCLUSION AND FUTURE WORK

This thesis has provided three important contributions. First, we built a rich dataset describing legislator’s activities on bills called the LAB dataset. This dataset was extracted from the Digital Democracy Project’s database, transformed using a Python pipeline, and segmented into three feature types: legislator features, bill features, and activity features. With over 1200 features, this dataset can be used in other research and analyses. For example, researchers could use this dataset for building a vote prediction model or analyzing how influential legislators over bill life cycles. Furthermore, this experiment was run using data from the 2015-2016 California State Legislature. We chose this session because California had the most complete feature set across all four state in Digital Democracy’s database. Unfortunately, we were unable to re-run our experiment on different states because of the unique differences in the data between states. Our data pipeline could be modified to collect data on other states. Finally, one of the goals of Digital Democracy Research Platform is to provide API’s for public access to their data. As future work, an API could be created for the project to access the LAB dataset and the embeddings we created.

Second, we produced meaningful embeddings from our novel neural network architecture called Democracy2Vec. This neural architecture allowed us to train our model with a full set of features but predict with a subset of those features. We trained this network to predict whether or not a legislator was a sponsor, if they spoke on a bill, and if their sentiment towards the bill was not neutral. During training, we used the legislator, bill, and activity features from our LAB dataset then we predicted on our entire data set just using legislator and bill features. From this network, we extracted embeddings that uniquely describe a legislator and how they are likely to act on a bill. In general, embeddings are extremely valuable and can be

applied to a variety of use cases [29][21][32]. Some future work with these embeddings can include using them as input to a vote prediction model. Additionally, researcher can investigate the other embeddings created from predictions using legislator and activity features and bill and activity features. An example of future work for these embeddings can be using the embeddings as input into a model that predicts if a bill will pass or if the bill needs to be revised. Another direction for future work could be investigating sponsorship prediction. Our network also predicted sponsorship quite well considering the size and sparse nature of our dataset. This could be beneficial when writing or editing a bill to see predict which legislators would support it. Finally, given that this is a novel network, future work should also test this network with a more balanced data set and in different domains. An example of an applicable domain could be in the medical field. Our model could potentially be trained using three medical measurements as input and the output for our dual embeddings could be the missing measurement. If successful, given two medical measurements, our model could predict the third.

Our third contribution is the case study we ran to explain and verify the meaning of our embeddings. This case study showed that our embeddings explained how legislators were likely going to act on a bill over a session. With these embeddings, we saw clusters of house, party, and political interest.

Overall, we believe that these contributions can be a stepping stone for political research. All of the code and data files for our LAB dataset, data pipeline, Democracy2Vec, and our embeddings have been given to the Digital Democracy Project and they will be publicly available on their Github repo [30]. We hope to see researchers use these contributions as powerful and effective inputs for their work.

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