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A thesis submitted in partial fulfilment

of the requirement for the degree of Doctor of Philosophy

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Cardiff University
School of Computer Science & Informatics

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To People you care
for their patience and support.

Abstract

We produce interpretable representations, and demonstrate their applicability in interpretable classifiers. Our approach is model-agnostic, given a similarity-based representation, we are able to produce a representation in terms of domain knowledge. We evaluate the interpretability of our representation and provide examples of interpretable classifiers with our representation.

Acknowledgements

Contents

List of Publications

The work introduced in this thesis is based on the following publications.

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List of Acronyms

ML Machine Learning

NLP Natural Language Processing

NDCG Normalized Discounted Cumulative Gain

0.0.1 Definitions

Domain Where the data was originally sourced from DOM^IMDB, e.g. IMDB movie reviews.

Word A string of alphanumeric characters that originated from text in the domain DOM_w, e.g. the $w = "Horror"$ from a domain of IMDB movie reviews DOM^IMDB.

w

Corpus of Documents A unique group of words, e.g. a review from a domain of IMDB movie reviews DOM_IMDB.

C_dw

Document A document of words

d_w

Vector Space A representation composed of vectors.

S_v

Semantic Space A representation where spatial relationships between vectors correspond to semantic relationships.

S_v

Word frequency The frequency of a word wf for its document D_wf.

wf

Bag-Of-Words a matrix BOW of documents BOW_D where each document is composed of unordered frequencies of words $D = [wf_1, ..., wf_n]$. and Conceptual Space we obtain a representation of entities composed of properties. Then, we cover the additional methods we propose to improve this process.

BOW_d

Bag-Of-Words PPMI

Feature A feature is a distinct useful aspect of the domain, corresponding to a numerical value.

R_f

Hyper-plane The hyper-plane for a word

H_w

Direction vector The orthogonal direction to a hyper plane that separates a word in a vector space.

D_w

Cluster label A cluster of words that describe a property.

C_w

Cluster direction The averaged directions of all words in the label.

D_C

Feature rankings The rankings induced from a feature direction.

R_DC

Chapter 1

Introduction

1.1 Motivation

With the rise of services on the web that enable large-scale user-generation of text data, e.g. Social Media sites (Facebook, Twitter), Review sites (IMDB, Rotten Tomatoes, Amazon) and content-aggregation sites (Reddit, Tumblr), the internet has become largely populated by text posts that are related to some specific, niche topic within a domain. For example, a review on Amazon for a product is specially tailored text for that product within the domain of Amazon reviews. Taken from a closer lens, we could even argue that each review-type has its own domain, e.g. Product reviews, Food reviews, Movie reviews. However, the text posts themselves are largely unstructured semantically. Humans can have an intuitive understanding of the semantics that are present in unstructured text, but machines do not.

One task of Natural Language Processing is to obtain this semantic understanding from text by obtaining a machine-readable representation that contains domain knowledge. A basic approach to obtain a representation of this text is to represent entities (e.g. reviews, text-posts) by the frequency of their words, see 1.1.

Below, we show a review with its associated properties labelled.

We can understand these properties to have a degree to which they apply, for example the size of the clothing might be "XXL", "XL", "L", "M" or "S", or the quality may be "Very good", "Good", "Ok", "Bad" or "Very bad". For the former, we may rely on the metadata available from the site itself, but for the latter the way to obtain this information is less clear. Although we may infer that the rating has some indication of these properties, it does not describe the properties or the degree to which the review refers to them. This kind of information is valuable

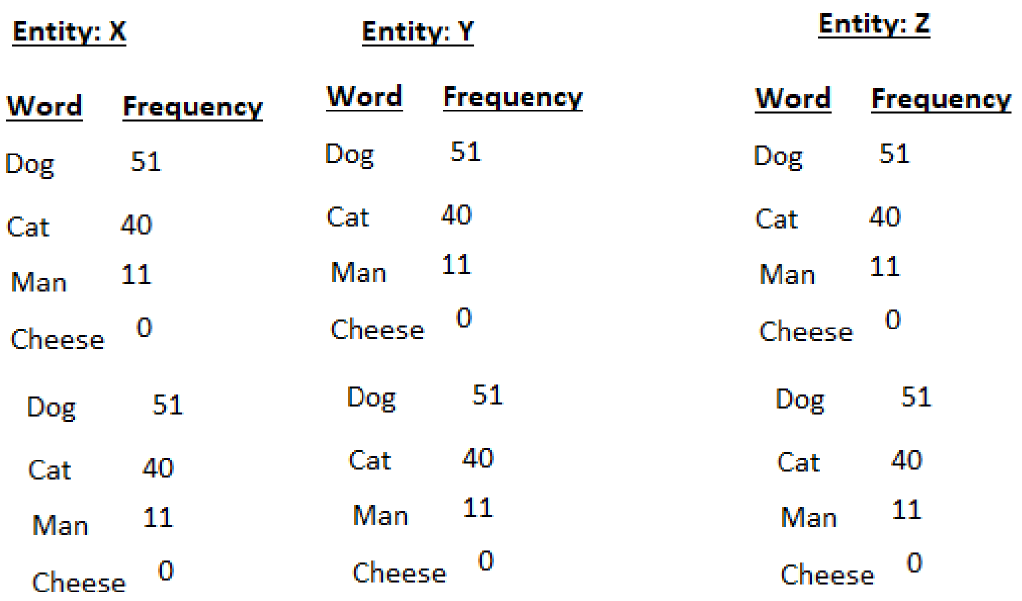


Figure 1.1: Bag-of-words

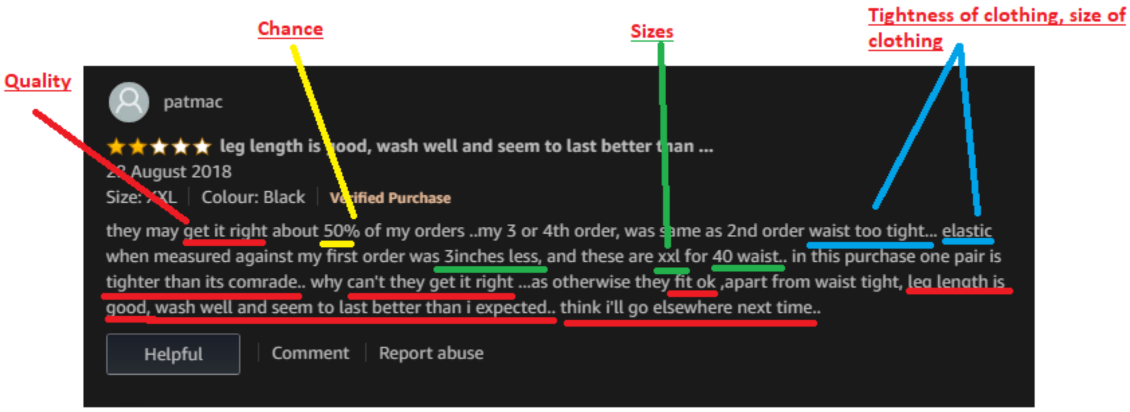


Figure 1.2: Example properties

for making sense of the world of unstructured text, and has broad applications, e.g. The most immediate example is perhaps that they allow for a natural way to implement critique-based recommendation systems, where users can specify how their desired result should relate to a given set of suggestions [?]. For instance, [?] propose a movie recommendation system in which the user can specify that they want to see suggestions for movies that are "similar to this one, but scarier". If the property of being scary is adequately modelled as a direction in a semantic space of movies, such critiques can be addressed in a straightforward way. Similarly, in [**?**] a system was developed that can find "shoes like these but shinier", based on a semantic space representation that was derived from visual features. Semantic search systems can use such directions to interpret queries involving gradual and possibly ill-defined features, such as "*popular* holiday destinations in Europe" [**?**]. While features such as popularity are typically not encoded in traditional knowledge bases, they can often be represented as semantic space directions.

1.1.1 Directions

However, manually labelling these properties and the degrees to which entities (e.g. reviews, text-posts) have them is extremely time-consuming.

A potentially ideal system would be as follows: We collect large amounts of unstructured text data, separated into domains, and obtain the properties of each domain from this data, and rank entities on the degree to which they have these properties. In this way, properties would be understood on a scale built from the domain directly, so that each domain has its own meanings for words according to their own idiosyncrasies. As the process does not require any manual labelling the quality of these properties could be improved simply by obtaining more data. Further, as we are learning from unstructured data, not only would this allow us to understand the data in terms of what we know, but it would also introduce us to new ideas that we may not have previously understood. This kind of representation also has value in application to Machine Learning tasks. If we can separate the semantics of the space linearly into properties, we are able to learn simple linear classifiers that perform well.

Simple linear classifiers built from a representation composed of rankings on properties have an additional benefit of being more understandable.

1.2 Interpretability

Most successful approaches in recent times, like vector-spaces, word-vectors, and others, rely on the distributional model of semantics. This model relies on encoding unstructured text e.g. of a movie review, as a vector, where each dimension corresponds to how frequent each word is, we are able to calculate how similar the entities are, e.g. we know that if two movies have a similar distribution of words in their reviews, like frequent use of the word ’scary’, or ’horror’, then they would have a higher similarity value. These models, also known as ’semantic spaces’ encode this similarity information spatially.

Semantic relationships can be obtained from semantic spaces.

applications/need for good interpretability:

- Safety
- Troubleshooting, bug fixing, model improvement
- Knowledge learning
- EU’s "Right to explanation"
- Discrimination

properties of an interpretable classifier:

- Complexity: ’the magic number is seven plus or minus two’ [5] also has many positive effects for its users, like lower response times [4, 2], better question answering and confidence for logical problem questions [2] and higher satisfaction [4].
- Transparancy:
- Explainability:
- Generalizability:

Properties, entities, the benefits and application of a representation formed of these

Basic introduction to directions, explanation of the utility and application of our approach

1.3 Thesis Overview / Contributions

In 3, we focus on further experimenting with one relationship that was formalized in [1]: a ranking of entities on properties. In particular, we use this method of building a representation of entities as a way to convert a vector space into an interpretable representation, for use in an interpretable classifier. The reason that we chose this representation to expand on is because by representing each entity e with a vector v that corresponds to a ranking r, the meaning of each dimension is distinct, and we are able to find labels composed of clusters of words for these dimensions. Here, we make the distinction between a property and a word, a property is a natural property of the space that exists in terms of a ranking of entities, and words are the labels we use to describe this property.

Chapter 2

Background

2.1 Text Representations

Need to write about the concept of salient features of a domain here.

2.1.1 Bag-of-words

We begin by processing an unstructured text corpus, composed of documents C_D. We then remove all punctuation, convert any accented characters to non-accented characters, and lower-case the documents to obtain word tokens for each document D_W. From here, we can assume that any $W \approx W$ will now $W = W$, if a word varied in format but not alphanumeric characters.

Then, we count the occurrences of each word

- Frequency
- Tf-idf
- PPMI

2.2 Text classification

2.2.1 Decision Trees

- Explanation of what decision trees are

- Explanation that they may not perform well on sparse information
- Max features
- Criterion
- CART decision trees versus others

2.2.2 Support Vector Machines

- Performance increase for support vector machines on sparse data, balancing, etc
- C parameters, gamma parameters

2.2.3 Neural Networks

- Difference between SVM and Nnet

2.2.4 Semantic Spaces

Bag-Of-Words representations of text result in large sparse vectors for each document,

How do vector spaces represent semantics? Why do we use them to represent semantics?

Distributional representations of semantics, known as 'semantic spaces' are well-recognized for their ability to represent semantic information spatially. These representations have been widely adopted for Natural Language Processing (NLP) tasks thanks to their ability to represent complex information in a dense representation. In particular, entity-embeddings have been applied to represent items in recommender systems [**?**, **?**, **?**], to represent entities in semantic search engines [**?**, **?**], or to represent examples in classification tasks [**?**].

Vector spaces are a popular way to represent unstructured text data, and have been broadly applied to and transformed by supervised approaches. They vary in method, producing structure from Cosine Similarity, Matrix Factorization, Word-Vectors/Doc2Vec, etc. They also vary in how they linearly separate entities. However, their commonality is that they are able to represent semantic relationships spatially. See Section 2.2.4 This brings up an essential point: When using a semantic space, are we taking advantage of relationships that are discriminative or incorrect? The danger of relying on these spaces and the models that use them has greatly affected their adoption in critical application areas like medicine, and has raised legal concerns about their application in e.g. determining if someone is suitable for a loan.

See Section 2.2.4

- Word-vectors

2.2.5 Document Representations

LSA

Principal Component Analysis is a dimensionality reduction method that results in dimensions ordered by importance. Starting with a large data matrix, e.g. our TF-IDF values from before, we first find the covariance matrix for these values. Then, from this covariance matrix we obtain the eigenvalues. We can then linearly transform the old data in-terms of this covariance matrix to obtain a new space of size equal to an arbitrary value smaller than our matrix.

- PCA
- MDS

2.3 Interpretable Representations

a. NNSE b. compositional c. 2007 paper as wikipedia similarities d. Topic models e. Infogan, etc

[**?**] Sparse PCA (Why not compare lol)

Vector space models typically use a form of matrix factorization to obtain low-dimensional document representations. By far the most common approach is to use Singular Value Decomposition [**?**], although other approaches have been advocated as well. Instead of matrix factorization, another possible strategy is to use a neural network or least squares optimization approach. This is commonly used for generating word embeddings [?, ?], but can similarly be used to learn representations of (entities that are described using) text documents [?, ?, ?]. Compared to topic models, such approaches have the advantage that various forms of domain-specific structured knowledge can easily be taken into account. Some authors have also proposed hybrid models, which combine topic models and vector space models. For example, the Gaussian LDA model represents topics as multivariate Gaussian distributions over a word embedding [?]. Beyond document representation, topic models have also been used to improve word embedding models, by learning a different vector for each topic-word combination [?].

The most commonly used representations for text classification are bag-of-words representations, topic models, and vector space models. Bag-of-words representations are interpretable in principle, but because the considered vocabularies typically contain tens (or hundreds) of thousands of words, the resulting learned models are nonetheless difficult to inspect and understand. Topic models and vector space models are two alternative approaches for generating low-dimensional document representations.

2.3.1 Word Vectors

Chapter 3

Converting Vector Spaces into Interpretable Representations

3.1 Introduction

The ever more pervasive digital infrastructure that supports our lives has resulted in many opportunities to obtain data and models to make sense of that data. Semantic Spaces that encode semantic relationships between documents spatially have recently achieved strong results on tasks like X, Y, Z. These neural-network learned representations make use of a variety of new information like grammatical structure, word-context and even image data. Further, as domains become more entrenched in the digital world, the need for models in safety critical domains like medicine or legal domains like credit evaluation have increased the need for producing interpretable models, as well as interpretable representations. However, the dimensions of a semantic space do not correspond to human understandable features, and standard approaches to interpretable text representations do not match the performance of these methods. Ideally, we would obtain a representation that makes use of the rich semantic relationships from a high-performing semantic space, but also has dimensions corresponding to interpretable features. To this end, we aim to introduce in this chapter a methodology to linearly transform a semantic space using just its associated bag-of-words as input into an interpretable representation, and demonstrate the applicability of this interpretable representation to simple interpretable classifiers.

There are many types of semantic relationships in a semantic space. For our work, the representation is composed of rankings of documents on semantic directions in the space, in particular where those directions correspond to features. We show an example of the kind-of directions we use to obtain our representation in 3.1. Directions from domain-specific semantic spaces have

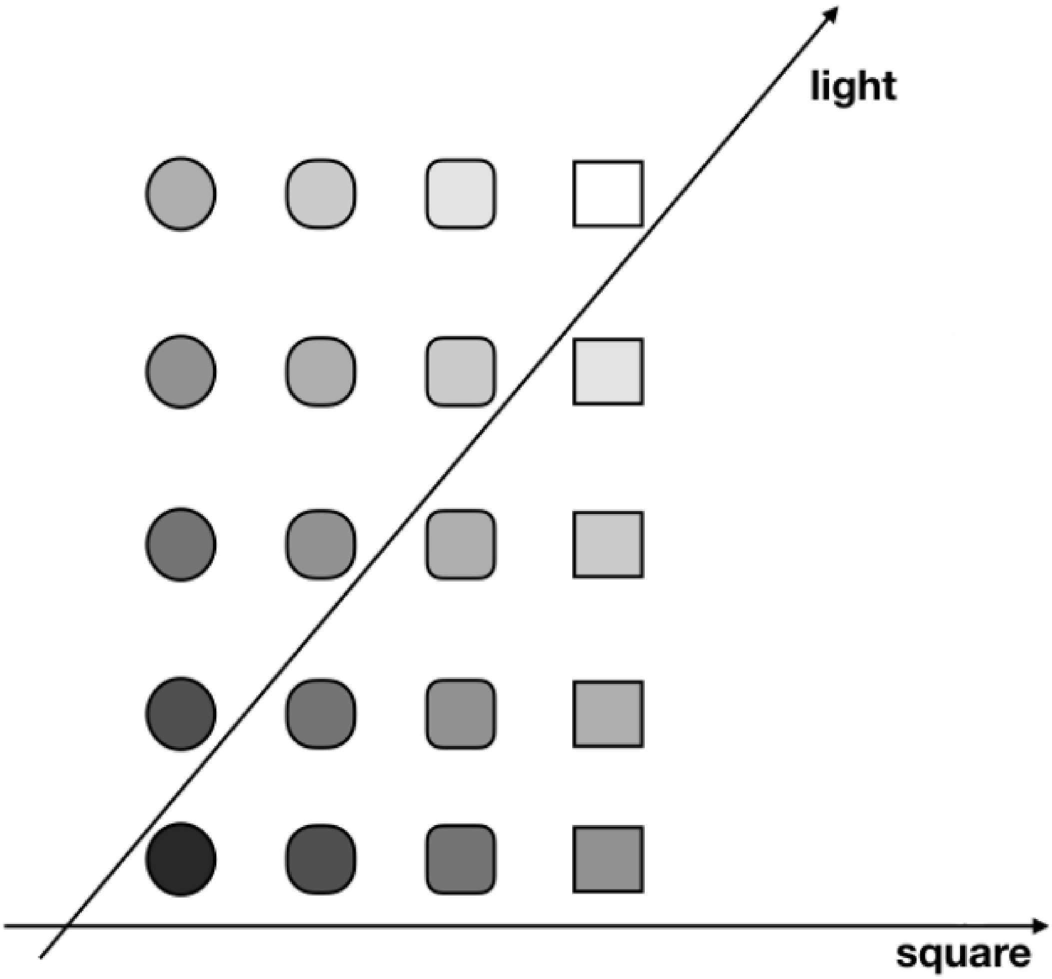
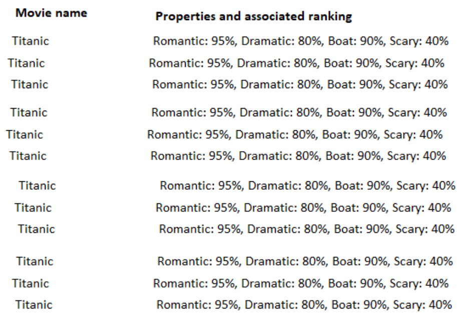


Figure 3.1: An example in a toy domain of shapes.

been used previously in a variety of ways, For instance, [?] found that features of countries, such as their GDP, fertility rate or even level of CO_2 emissions, can be predicted from word embeddings using a linear regression model. Similarly, in [?] directions in word embeddings were found that correspond to adjectival scales (e.g. bad $<$ okay $<$ good $<$ excellent) while [?] found directions indicating lexical features such as the frequency of occurrence and polarity of words.

Derrac [1] introduced an unsupervised method to go from a semantic space and its associated bag-of-words to a representation where each dimension is a ranking of documents on a feature of the domain. For example, in the domain of movie reviews genres would be a feature, and the dimension would have a numeric value for each document corresponding to the degree it is a particular genre. The contribution of this Chapter is an analysis and experimentation on the and rep.png



Movie name	Properties and associated ranking
Titanic	Romantic: 95%, Dramatic: 80%, Boat: 90%, Scary: 40%
Titanic	Romantic: 95%, Dramatic: 80%, Boat: 90%, Scary: 40%
Titanic	Romantic: 95%, Dramatic: 80%, Boat: 90%, Scary: 40%
Titanic	Romantic: 95%, Dramatic: 80%, Boat: 90%, Scary: 40%
Titanic	Romantic: 95%, Dramatic: 80%, Boat: 90%, Scary: 40%
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Titanic	Romantic: 95%, Dramatic: 80%, Boat: 90%, Scary: 40%
Titanic	Romantic: 95%, Dramatic: 80%, Boat: 90%, Scary: 40%

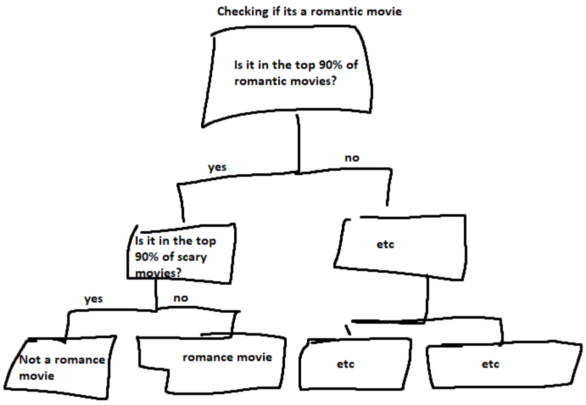

Figure 3.2: Example movies and selected associated dimensions, chosen according to their relevance to the genre task..

quality of these features applied to document classification. The main insight from our work is that these interpretable features do not suffer a performance drop in a non-linear classifier compared to the original representation, and can outperform the original representation and a baseline interpretable representation in a linear classifier. In addition, we find that if a dimension ranks documents on a feature relevant to the task, it can be competitive with more complex models using a single decision tree node. We show an example of the representation from a domain of IMDB movie reviews in 3.2.

This chapter continues as follows: We begin by describing related work, then explain the method, making explicit the variations we have introduced for our experimental work. We follow this with the results of our experiments accompanied by qualitative examples and explanations, and finish with a conclusion on the benefits and limitations of this approach.

These relationships have been expanded on, for example [6] found that "equivalent relations tended to correspond to parallel vector differences" [3], and [3], found that by decomposing representations into orthogonal semantic and syntactic subspaces they were able to produce substantial improvements on various tasks. Additionally, they have also been found to hold inherent gender bias [**?**] as word distances between gendered words (e.g. male, female, she, her) and occupational words e.g. (nurse, programmer) were correlated to the percentage of occupation that gender had for that role in different time periods.

3.2 Method

This section details the methodology to go from a Bag-Of-Words (BOW) 2.1.1 and Semantic Space 2.2.4, to rankings of documents on features of the domain, e.g. In a domain of IMDB movie reviews, where a document is composed of all of its reviews, a movie would be ranked on features like $Scary, Horror, Bloody$ and $Romantic, Love, Cute$, ideally with as many rankings as salient features of the domain.

3.2.1 Obtaining Directions and Rankings From Words

In this section we show how to obtain directions for words, and explain how to obtain document representations by ranking documents on these directions. For this step, we do not expect all words to be features of the domain. In the next sections, we aim to filter these words to obtain salient features.

Obtaining directions for each word For each word w, a Support Vector Machine (See Section 2.2.2) classifier is trained on the binary Bag-Of-Words representation of that word, where words are labelled as positive if they occurred more than once $w_f >= 1$ and negative otherwise. Although the separation of documents is binary, we can expect that the degree to which they are classified as the word varies. For example in a space constructed from frequency vectors, we can expect that the documents which contain the word more frequently would be further away from the hyper-plane in the positive direction. Following this, we can consider the vector v_w perpendicular to the hyperplane as the direction that models documents from least relevant at the distance furthest from the hyperplane on the negative side to most relevant for the word w at the distance furthest from the hyperplane at the positive side. We show an example of this in the toy domain in Figure 3.3.

Ranking documents on directions Once we have obtained a direction vector for each word v_w the next step is to quantify the degree to which each document has that word, by obtaining a value that corresponds to how far-up it is on the direction vector. These are our rankings of documents on words, if p_d is the representation of a document in the given vector space as a point then we can think of the dot product between the hyper-plane and the document vector $H_w \cdot p_d$ as the ranking $r_d w$ of the document d for the word w, and in particular, we take $r_d 1 < r_d 2$

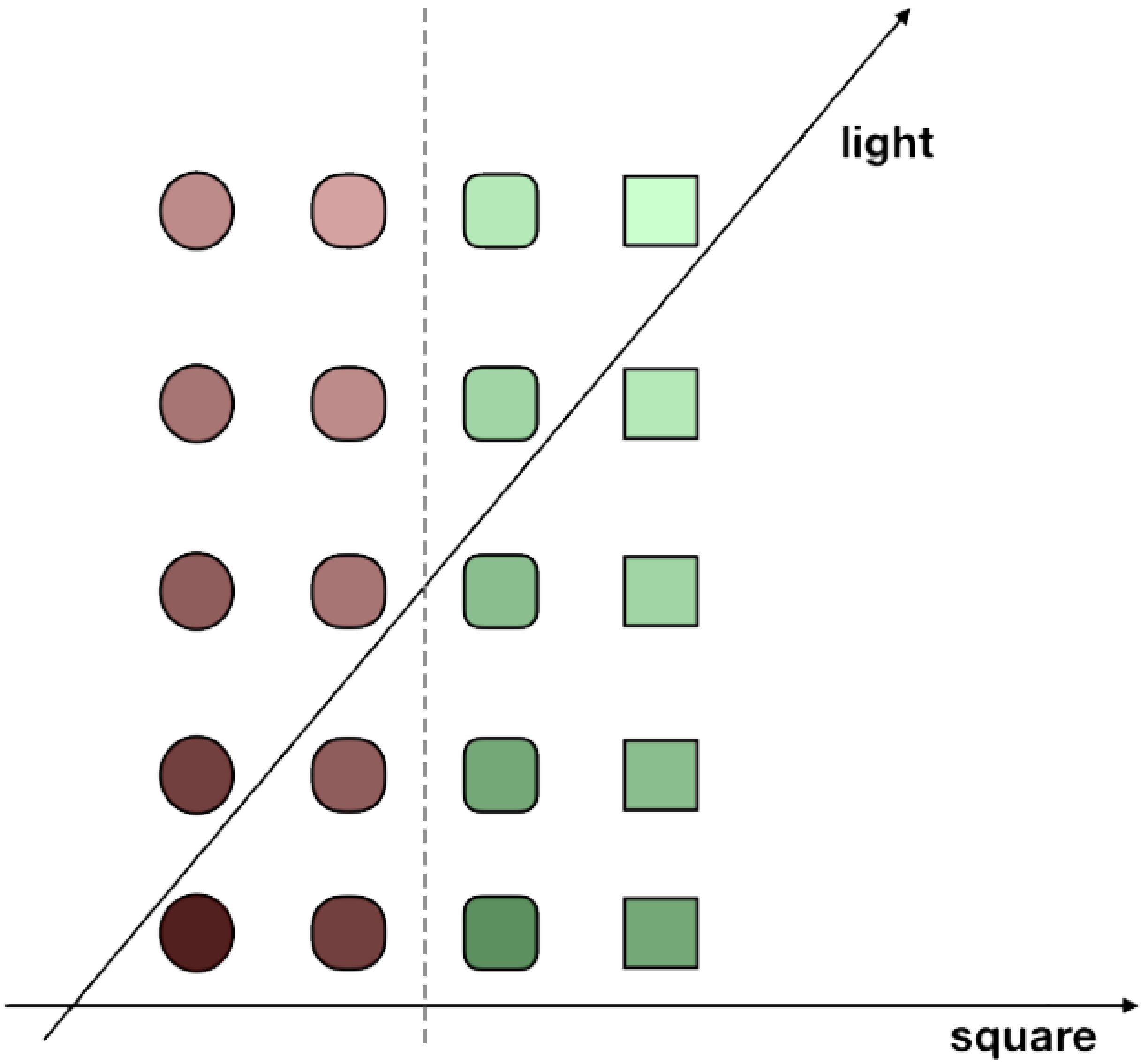

Figure 3.3: An example of a hyper-plane and its orthogonal direction in a toy domain of shapes. Green shapes are positive examples and red shapes are negative examples, but despite the problem being binary those closest to the hyper-plane are less defined than those further away, resulting in the orthogonal vector being a direction..

to mean that d_2 has the property labelled with the word w to a greater extent than e_1. Below, we show some examples of features and documents ranked on them for different domains.

3.2.2 Filtering Words

With the rankings R_r, we could create a representation of each document d, composed of w_n dimensions, where each dimension is a ranking of the document d on that word $r_d w$. However, many of the words are not spatially important enough in the representation to result in a quality ranking - they are not salient features. In this section, we aim to filter the words that are not separable, we evaluate them using a scoring metric, and remove the words that are not sufficiently well scored. We use three different metrics:

Classification accuracy. Evaluating the quality in terms of the accuracy of the SVM classifier: if this classifier is sufficiently accurate, it must mean that whether word w relates to document d (i.e. whether it is used in the description of d) is important enough to affect the semantic space representation of d. In such a case, it seems reasonable to assume that w describes a salient property for the given domain.

Cohen's Kappa. One-kind of feature we find in these domains are binary labels of documents, for example a movie either is or isn't a movie with "Gore". We can expect that the more salient a binary feature, the more linearly separable it will be in the space. One problem with accuracy as a scoring function is that these classification problems are often very imbalanced. In particular, for very rare words, a high accuracy might not necessarily imply that the corresponding direction is accurate. For this reason, [1] proposed to use Cohen's Kappa score instead. In our experiments, however, we found that accuracy sometimes yields better results, so we retain Kappa as an alternative metric.

Normalized Discounted Cumulative Gain This is a standard metric in information retrieval which evaluates the quality of a ranking w.r.t. some given relevance scores [**?**]. In our case, the rankings r_d of the document d are those induced by the dot products $v_w \cdot d$ and the relevance scores are determined by the Pointwise Positive Mutual Information (PPMI) score *ppmi*(w, d), of the word w in the BoW representation of entity d where *ppmi*$(w, d) = \max\left(0, \log\left(\frac{p_{wd}}{p_{w*} \cdot p_{*d}}\right)\right)$, and

$$p_{wd} = \frac{n(w, d)}{\sum_{w'} \sum_{d'} n(w', d')}$$

where $n(w, d)$ is the number of occurrences of w in the BoW representation of object d, $p_{w*} = \sum_{e'} p_{wd'}$ and $p_{*d} = \sum_{w'} p_{w'd}$.

By scoring the words on these features, we can apply a simple cut-off (e.g. the top 2000 scored words) to obtain the most salient words. Ideally, this cut-off would be at the point where the words stop corresponding to salient features. However, it is difficult to determine this. In principle, we may expect that accuracy and Kappa are best suited for binary features, as they rely on a hard separation in the space between objects that have the word in their BoW representation and those that do not, while NDCG should be better suited for gradual features. In practice, however, we could not find such a clear pattern in the differences between the words chosen by these metrics despite often finding different words. In Table **??**, we show examples of the differences between the largest differences between the scoring methods.

Clustering Direction Vectors

If we consider two directions, "Blood" and "Gore", we can understand both of these to be approximating a similar feature of movies, as they both relate to how much blood a movie contains. Because of this, we can expect their directions to be very similar to each other. This is the first idea behind clustering these directions, if we average these directions together we can obtain a direction inbetween them that is a balance between documents that used the word 'Bloody' to describe the blood and the word 'Gore'. To expand on this, some entities would have the property of being bloody films, but did not necessarily use the term gore in their reviews, same as some entities having the property but using the term gore not bloody, we can understand that this new hyper plane and associated direction more accurately represents the property of a bloody film more than either of the terms individually. By extending this to a clustering method, we can find similar abstract features by ensuring that all similar directions are clustered together.

The word direction for "beautiful" can be nebulous to the interpreter, as it is not clear what it means for a movie to be ranked highly on 'beautiful'. Considering this, clustering provides another advantage, once we cluster the terms to find the property ("beautiful", "cinematography" "shots") we are given context for the word and more easily intuit the feature, in this case it is a feature about how well the movie was directed.

We approach clustering the directions with a variety of methods:

K-Means K-Means is a clustering algorithm that starts with determining the amount of clusters, K. To begin, K centroids c are randomly placed into the space. Then, the distance between each point p and centroid c (in our case, points are determined by rankings) is calculated. Each point p is then assigned to its closest centroid c. Then, the centroids are recomputed to be the mean of their assigned points. This process starting with the distance calculation is repeated until the points assigned to the centroids do not change.

Derrac's K-Means Variation This is the clustering method used in the previous work [**?**]. As input to the clustering algorithm, we consider the N best-scoring candidate feature directions v_w, where N is a hyperparameter. The main idea underlying their approach is to select the cluster centers such that (i) they are among the top-scoring candidate feature directions, and (ii) are as close to being orthogonal to each other as possible.

The output of this step is a set of clusters $C_1, ..., C_K$, where we will identify each cluster C_j with a set of words. We will furthermore write v_{C_j} to denote the centroid of the directions corresponding to the words in the cluster C_j, which can be computed as $v_{C_j} = \frac{1}{|C_j|} \sum_{w_l \in C_j} v_l$ provided that the vectors v_w are all normalized. These centroids $v_{C_1}, ..., v_{C_k}$ are the feature directions that are identified by our method.

We choose our first cluster centroid by taking the top-scoring direction for its associated metric. Then, we select centroids until we have reached the desired amount by taking the maximum of the summed absolute cosine similarity of all current centroids, in other words taking the most dissimilar direction to all of the current directions. Once we have selected the centroids, for each remaining direction we find the centroid it is most similar to, and the centroid is updated once the direction has been added.

3.3 Quantitative Results

3.3.1 Datasets

We use five different domains:

Newsgroups, originally containing 18,846 documents, is preprocessed using sklearn to remove headers, footers and quotes. Then, empty and duplicate documents are removed, resulting in 18302 documents. The vocabulary size is 141,321. The data is not shuffled. After filtering out terms that did not occur in at least two documents, we ended up with a vocabulary of size 51,064.

Sentiment is dataset where documents are reviews, containing 50,000 documents with a vocabulary size of 78588. After removing terms that did not occur in at least two documents, we ended up with a vocab of size 55384. Notably, this means that we removed all terms that did not occur in two documents for the sentiment, and in two documents for the newsgroups, and newsgroups began with a larger vocabulary than sentiment, but the ending vocabularies were about the same. This means that the terms in the newsgroups were more sparse than sentiment. In other words, newsgroups contained many terms that were not relevant to a majority of the documents. This is unsurprising, as it is a collection of 20 different newsgroups, rather than one single domain.

Reuters is a dataset of reuters news wires, originally containing 10788 documents. After removing empty and duplicate documents, we end-up with 10655 documents. It originally contained 90 classes, but as they were extremely unbalanced we removed all classes that did not have at least 100 positive instances, resulting in 21 classes. All other classes in other domains meet this threshold. The original vocabulary size is 51,0001, and after removing all words that do not occur in at least two documents, the vocabulary size is 22542.

Placetypes is a data-set of flickr tags, taken from the previous work [1]. It originally has a vocabulary size of 746,527 and 1383 documents. This is a very large vocabulary size to document ratio. The end vocabulary for this space was 100,000, which we used as a hard limit. This is roughly equivalent to removing all documents that would not be in at least 6 documents.

Movies is a dataset where each document is a movie represented by all of its reviews concatenated across a number of sources. It starts off with a vocabulary size of 551,080 and a document size of 15,000. However, after investigating the data made available by the authors, we found that there were a number of duplicate documents. After removing these duplicate documents, we end-up with 13978 documents. In the same way as the movies, we limit the vocabulary size at 100,000.

For all of these datasets, we split them into a 2/3 training data, 1/3 test data split. We additionally remove the end 20% of the training data and use that as development data for our hyper-parameters, which is then not used for the final models verified using test data.

3.3.2 Evaluation Method

We primarily examine the effectiveness of a representation on its ability to perform in low-depth Decision Trees, specifically CART Decision Trees (See Background Section 2.2.1) with a limited depth of one, two and three. We enter this evaluation with a few assumptions: A good interpretable representation disentangles salient domain knowledge into its dimensions, and natural domain tasks (e.g. classifying genres of movies using their reviews) can be evaluated effectively using that salient domain knowledge. Put another way, if the space is representing domain knowledge well we can expect that the space is linearly separable for key semantics of the domain. In spatial terms, a representation will be capable of being linearly transformed by our method into these distinct relevant concepts if semantically distinct entities are spatially separated, and semantically similar entities are close together.

If we only wanted to evaluate the quality of the representation, we could use Linear SVM's to find the hyper-planes that effectively separate these spatial representations for the class. However, the representations that encode this spatial information are not interpretable, so a linear classifier although able to separate the documents that contain the class and do not contain them will not be interpretable either. It is our main interest to evaluate how well a representation encodes these key semantics while also being restricted by the requirement to be disentangled into words or clusters, in other words how well it represents the information while also being interpretable.

Given these assumptions, low-depth decision trees can give an estimation of how good an interpretable representation is. If the representation cannot perform for a class at a one-depth tree, then it is not disentangled such that it contains a single salient dimension that effectively evaluates a class. If a representation cannot perform well on two-depth trees, then the representation is not disentangled into three concepts that can sufficiently determine that class, and if a representation cannot perform well on three-depth trees, it has not disentangled the representation such that there are nine relevant concepts that are relevant to that class. To see what these different trees look like see figure 3.4. A comparison to put this in better perspective is to an unbounded tree. Unbounded trees select a large amount of dimensions in order to achieve a performance difference on development data, but when applied to test data the models do not generalize well. This is because they overfit, rather than using the key semantics of the space to

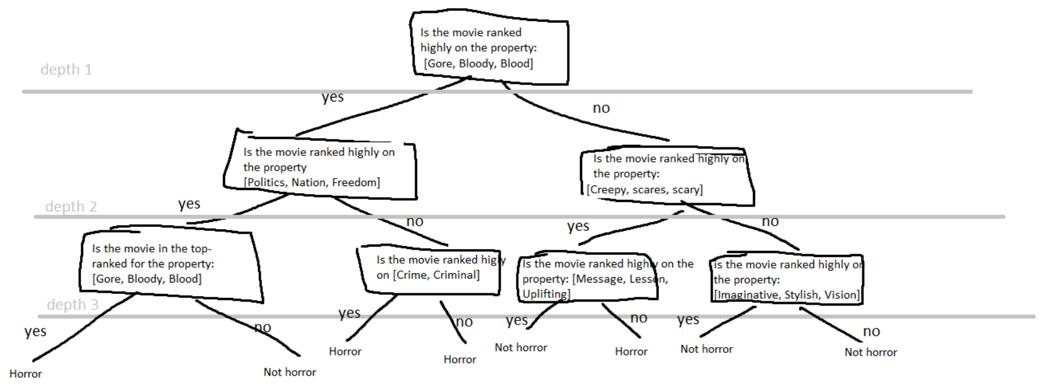

Figure 3.4: This figure shows an example tree from one of our classifiers. Here, we can see that the model increases in complexity as it increases in depth. In this case, we end-up getting better F-score with just a depth-one tree, as the tree begins to overfit at depth three. .

classify.

We look primarily at the F1-score to determine if a classifier is good or not. This is because many of the classes are unbalanced (See above in Section 3.3.1 for exactly how unbalanced) so accuracy is not a good metric, as high accuracy could be achieved by predicting only zeros. All of the results shown in this section are the end-product of a two-part hyper-parameter optimization. Each Decision Tree has its own set of hyper-parameters that are optimized as does each representation-type. These are the models trained on the training data and scored on the test data, with the highest performing in terms of F1-score parameters from hyper-parameter optimization on the development data. For ease of comparison, we provide some results with SVM's and unbounded Decision Trees, as well as a baseline Topic Model, which we use as a reference for a standard interpretable representation. Below, we list the parameters that we optimize for each of these model types:

Linear Support Vector Machines (SVM's): **Topic Models**:**CART Decision Trees** :

Multi-Dimensional Scaling (MDS): **Principal Component Analysis (PCA)**: **Doc2Vec (D2V)**: **Average Word Vectors (AWV)**:

When obtaining the single word directions, we take all of the baseline representations and vocabularies, and filter the vocabularies according to a hyper-parameter that we tune. As the

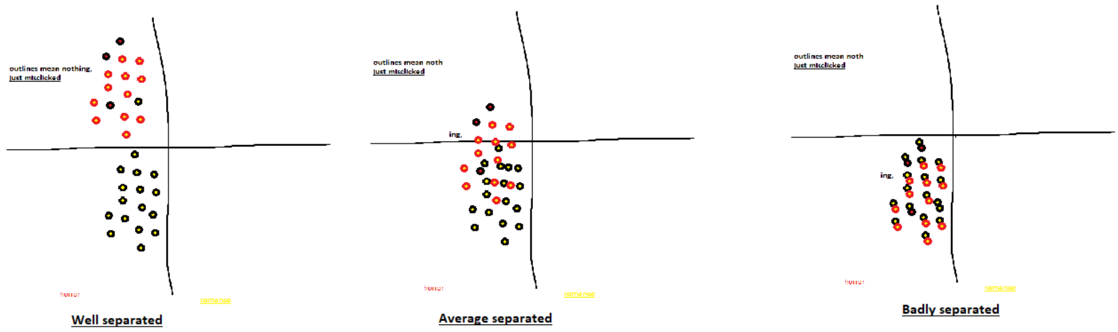

Figure 3.5: A conceptual space of movies, where regions correspond to properties and entities are points..

doc2vec has already been hyper-parameter optimized, we use the optimal doc2vec space that scored the highest for its class on a Linear SVM, rather than tuning the entire process around the doc2vecs vectors. So for example, when we are evaluating the Keywords task for the movies, we would obtain directions from the doc2vec space that performed best for a linear SVM on the Keywords task following the previous experiments.

The parameters were We are not able to obtain an MDS space for sentiment or doc2vec spaces for placetypes/movies.

For example, a good vector space in the domain of movies constructed from IMDB movie reviews should contain a natural separation of entities into genres, where Horror movies are spatially distant from Romance movies, and movies that are Romantic Horrors would be somewhere inbetween. We can see an example in Figure 3.5. For a Bag-Of-Words, we can expect similar entities to have similarly scoring terms **??**.

We obtain results for the rankings induced from these word directions on Decision Tree's limited to a depth of 3 in-order to select the best parameters when using directions for each class. The parameters that we want to determine are the type of Semantic Space, the size of the space, the frequency threshold and the score threshold. To do so, for each space-type of each size, we use a grid search to find the best frequency and score cut-offs for that sized space-type. Then, we select from these space-types and sizes the best performing one. We can understand there to be a balance between finding words which are useful for creating salient features in our clustering step without including too many words which do not. As our clustering methods are unsupervised, it is important that we try and limit the amount of junk being entered into them,

	Top PPMI scoring terms
Example Horror Entity	Term term term term term term term term term term term term term term
Similar Horror Entity	Term term term term term term term term term term term term term term
Somewhere Inbetween Entity	Term term term term term term term term term term term term term term
Romance Movie	Term term term term term term term term term term term term term term
Similar Romance movie	Term term term term term term term term term term term term term term

Table 3.1: Two of the following entities: Those classified as horror, those classified as horror and romance, and those classified as romance with their associated highest value PPMI terms. We show the highest positive instances here as the representation is sparse, even though we can also expect the terms that are low scoring to be similar too..

despite the classifiers that use these directions typically being able to filter out those directions which are not suitable to the class. Additionally, as the vocabulary size varies from dataset to dataset, the threshold will naturally be different for each one.

These results allow us to choose for each class, the best Semantic Space and Scoring-type for that class. Next, we test single directions, attempting to find a good amount of directions to cluster and not including words which may hamper the unsupervised classification, as well as the best space-type for each domain. We found that generally, X was the best space and as expected classifiers performed better with more data, so we use 20000 as our frequency cutoff and 2000 as our score cutoff.

We continue with the optimal space and score-type chosen by our single direction experiments, and use the same frequency and score thresholds as before. We then experiment with two different clustering algorithms: Derrac and K-Means. As these algorithms select centroids from the top-scoring directions or randomly, we can expect that some clusters may not be salient features of the space. This is because top-scoring directions, e.g. for accuracy could simply infrequent terms that do not have much meaning, and these infrequehnt terms could also be randomly selected. We could use grid-search on the frequency and score cutoffs when obtaining these results in order to avoid terms that may disrupt existing clusters or form cluster centers that are not salient features of the space, but we chose a more standardized process that would rely on the parameters of the clustering algorithms and the ability of the classifiers to filter out clusters that are not informative, so as to not make a time-costly grid search a necessary part of the process.

With that in mind, we use three clustering algorithms.

Mini batch K-means, implemented by scikit-learn [1], introduced by [**?**] and kmeans++ to initialize [**?**]

3.3.3 Summary of all Results

To begin, we compare the original dimensions of the space, the rankings on single words, the rankings on cluster directions, a bag-of-words of PPMI scores and

[1] https://scikit-learn.org/stable/modules/generated/sklearn.cluster.MiniBatchKMeans.html

	Genres			Keywords			Ratings		
Movies	D1	D2	D3	D1	D2	D3	D1	D2	D3
Space	0.301	0.358	0.354	0.185	0.198	0.201	0.463	0.475	0.486
Single directions	**0.436**	0.463	0.492	0.23	**0.233**	**0.224**	0.466	0.499	0.498
Clusters	0.431	**0.513**	**0.506**	0.215	0.22	0.219	**0.504**	**0.507**	**0.513**
PPMI	0.429	0.443	0.483	**0.243**	0.224	0.224	0.47	0.453	0.453
Topic	0.415	0.472	0.455	0.189	0.05	0.075	0.473	0.243	0.38
	Newsgroups			Sentiment			Reuters		
	D1	D2	D3	D1	D2	D3	D1	D2	D3
Rep	0.251	0.366	0.356	0.705	0.77	0.773	0.328	0.413	0.501
Single dir	0.418	**0.49**	**0.537**	0.784	0.814	**0.821**	**0.678**	**0.706**	0.72
Cluster	0.394	0.433	0.513	0.735	**0.844**	0.813	0.456	0.569	0.583
PPMI	0.33	0.407	0.444	0.7	0.719	0.73	0.616	0.699	**0.723**
Topic	**0.431**	0.423	0.444	**0.79**	0.791	0.811	0.411	0.527	0.536
	Foursquare			OpenCYC			Geonames		
Placetypes	D1	D2	D3	D1	D2	D3	D1	D2	D3
Rep	0.438	0.478	0.454	0.383	0.397	0.396	0.349	0.34	0.367
Single dir	**0.541**	0.498	**0.531**	0.404	**0.428**	0.39	**0.444**	**0.533**	**0.473**
Cluster	0.462	0.507	0.496	**0.413**	0.42	**0.429**	0.444	0.458	0.47
PPMI	0.473	**0.512**	0.491	0.371	0.351	0.352	0.361	0.301	0.242
Topic	0.488	0.433	0.526	0.365	0.271	0.313	0.365	0.3	0.219

Table 3.2: summary of all results

3.3.4 Baseline Representations

To begin, we show in Table 3.3 all variations of the baseline representations used directly as input to Decision Trees and SVM's. These examples that do not apply our methodology, serve as a reference point for what is possible using standard linear models without the need for interpretability. There is a big performance drop when going from depth three trees to depth one trees. These kind of performance drops are expected for these representations, as they do not have dimensions that correspond to key semantics, so it is unlikely that a smaller tree will be able to use the available dimensions to classify well. In this full table we include the precision and recall scores for clarity, mainly to explain why the high recall scores occur. This is because we balanced the weights as one of our hyper-parameters, and when the weight is balanced so that positive instances are weighted more heavily, the model prioritizes recall over precision. When this high recall score doesn't occur, that means that not balancing the weights performed better on the development data.

The size of the space is not as influential as the representation type in these results for the Decision Trees. For this reason we show only the best performing representation of each type in the main results table for this section. Although Linear SVM's perform the best on these representations without the need for interpretability, future results will be for low-depth decision trees in-order to easily distinguish the degree to which key semantics correspond to dimensions in the representations.

Newsgroups	D1				D2				D3				DN				SVM			
	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec
PCA 200	0.701	0.251	0.148	0.811	0.843	0.366	0.245	0.719	0.956	0.355	0.54	0.265	0.946	0.44	0.45	0.432	0.969	0.612	0.746	0.519
PCA 100	0.698	0.247	0.146	0.813	0.835	0.362	0.241	0.731	0.957	0.356	0.576	0.257	0.948	0.451	0.465	0.438	0.969	0.586	0.768	0.474
PCA 50	0.68	0.24	0.141	0.829	0.834	0.355	0.234	0.735	0.957	0.329	0.472	0.253	0.947	0.45	0.462	0.438	0.966	0.52	0.745	0.399
AWV 200	0.687	0.217	0.126	0.781	0.758	0.256	0.156	0.718	0.764	0.26	0.157	0.751	0.937	0.339	0.352	0.328	0.961	0.468	0.641	0.369
AWV 100	0.677	0.21	0.122	0.775	0.78	0.275	0.173	0.683	0.746	0.25	0.149	0.769	0.934	0.324	0.332	0.317	0.865	0.4	0.265	0.812
AWV 50	0.696	0.219	0.127	0.772	0.777	0.272	0.168	0.71	0.743	0.25	0.149	0.786	0.935	0.325	0.335	0.316	0.842	0.362	0.233	0.819
MDS 200	0.581	0.184	0.103	**0.837**	0.742	0.262	0.16	0.729	0.719	0.236	0.139	0.785	0.935	0.327	0.332	0.323	0.965	0.501	**0.802**	0.364
MDS 100	0.586	0.187	0.105	0.833	0.754	0.261	0.159	0.727	0.705	0.236	0.138	**0.808**	0.935	0.33	0.338	0.321	0.878	0.439	0.308	0.765
MDS 50	0.593	0.153	0.087	0.647	0.716	0.25	0.15	**0.756**	0.736	0.243	0.144	0.774	0.935	0.324	0.335	0.313	0.854	0.394	0.259	0.821
D2V 200	0.682	0.205	0.119	0.746	0.802	0.268	0.169	0.646	0.77	0.269	0.164	0.75	0.94	0.366	0.389	0.346	0.961	0.468	0.641	0.369
D2V 100	0.682	0.208	0.12	0.762	0.792	0.268	0.168	0.662	0.786	0.268	0.164	0.727	0.94	0.376	0.392	0.361	**0.971**	**0.628**	0.761	0.535
D2V 50	0.683	0.207	0.12	0.764	0.809	0.294	0.187	0.694	0.782	0.28	0.172	0.761	0.943	0.394	0.415	0.376	0.97	0.601	0.758	0.497
PPMI	**0.948**	0.33	**0.532**	0.239	0.947	0.407	0.511	0.338	0.944	**0.444**	0.506	0.396	**0.951**	**0.494**	**0.496**	**0.492**	0.962	0.613	0.627	0.599
Topic	0.852	**0.431**	0.304	0.743	**0.96**	**0.423**	**0.604**	0.326	**0.961**	0.444	**0.606**	0.35	0.944	0.432	0.434	0.429	0.879	0.46	0.318	**0.835**

Table 3.3: Full results for the newsgroups.

Table 3.4: Results for all other domains for the representations.

Reuters	D1		D2		D3		DN		SVM	
	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	0.847	0.328	0.917	0.413	0.978	0.501	0.978	0.565	0.989	0.761
AWV	0.782	0.252	0.971	0.328	0.974	0.417	0.973	0.495	0.987	0.719
MDS	0.791	0.263	0.9	0.357	0.979	0.489	0.976	0.522	0.988	0.67
D2V	0.818	0.268	0.867	0.298	0.974	0.445	0.971	0.482	0.986	0.724
PPMI	**0.975**	**0.616**	**0.978**	**0.699**	**0.98**	**0.723**	**0.984**	**0.746**	**0.99**	**0.8**
Topic	0.92	0.411	0.977	0.527	0.977	0.536	0.977	0.56	0.95	0.513

Sentiment	D1		D2		D3		DN		SVM	
	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	0.745	0.705	0.755	0.77	0.778	0.773	**0.781**	**0.779**	**0.891**	**0.893**
AWV	0.642	0.652	0.643	0.694	0.695	0.717	0.66	0.663	0.827	0.829
D2V	0.642	0.664	0.66	0.707	0.702	0.7	0.711	0.708	0.878	0.878
PPMI	0.616	0.7	0.655	0.719	0.675	0.73	0.712	0.71	0.887	0.888
Topic	**0.793**	**0.79**	**0.794**	**0.791**	**0.81**	**0.811**	0.733	0.73	0.815	0.822

Placetypes	D1		D2		D3		DN		SVM	
OpenCYC	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	0.586	0.346	0.708	0.343	0.695	0.342	0.832	0.309	0.847	0.474
AWV	0.625	**0.383**	0.651	0.376	0.728	**0.396**	**0.844**	**0.362**	0.85	0.466
MDS	0.624	0.364	0.7	**0.397**	0.731	0.374	0.843	0.305	0.861	**0.476**
PPMI	**0.728**	0.371	0.75	0.351	0.739	0.352	0.843	0.323	**0.9**	0.366
Topic	0.708	0.365	**0.87**	0.271	**0.87**	0.313	0.831	0.313	0.808	0.407

Movies	D1		D2		D3		DN		SVM	
Genres	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	0.722	0.301	0.755	0.339	0.717	0.321	0.884	0.372	**0.925**	0.518
AWV	0.679	0.29	0.774	0.321	0.756	0.343	0.873	0.312	0.922	0.496
MDS	0.679	0.298	0.79	0.358	0.773	0.354	0.887	0.385	0.875	**0.532**
PPMI	**0.852**	**0.429**	**0.91**	0.443	**0.912**	**0.483**	0.882	**0.416**	0.923	0.526
Topic	0.767	0.415	0.905	**0.472**	0.912	0.455	**0.889**	0.415	0.843	0.491

Placetypes	D1		D2		D3		DN		SVM	
Foursquare	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	0.731	0.342	0.823	0.393	0.86	0.388	0.887	0.398	0.896	0.568
AWV	0.767	0.401	0.828	0.478	0.85	0.452	0.905	**0.505**	0.923	**0.622**
MDS	**0.915**	0.438	0.804	0.427	0.86	0.454	0.893	0.462	0.932	0.619
PPMI	0.889	0.473	0.915	**0.512**	0.904	0.491	0.881	0.31	**0.938**	0.567
Topic	0.864	**0.488**	**0.916**	0.433	**0.917**	**0.526**	**0.907**	0.464	0.916	0.569

Movies	D1		D2		D3		DN		SVM	
Keywords	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	0.647	0.185	0.644	0.193	0.677	0.199	0.846	0.161	0.787	0.272
AWV	0.5	0.16	0.641	0.179	0.595	0.174	0.853	0.141	0.717	0.23
MDS	0.633	0.179	0.69	0.198	0.674	0.201	0.84	0.163	0.788	**0.28**
PPMI	**0.818**	**0.243**	0.745	**0.224**	0.739	**0.224**	0.847	**0.17**	**0.921**	0.217
Topic	0.629	0.189	**0.932**	0.05	**0.93**	0.075	**0.857**	0.152	0.678	0.21

Placetypes	D1		D2		D3		DN		SVM	
Geonames	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	0.502	0.301	0.69	0.305	0.68	0.295	0.821	0.243	0.844	0.401
AWV	0.657	0.326	0.755	0.323	0.842	**0.367**	0.813	0.332	0.865	**0.514**
MDS	0.626	0.349	0.695	**0.34**	0.796	0.272	**0.845**	0.295	0.638	0.397
PPMI	**0.808**	0.361	0.732	0.301	0.76	0.242	0.83	0.283	**0.894**	0.312
Topic	0.771	**0.365**	**0.863**	0.3	**0.85**	0.219	0.828	**0.348**	0.819	0.349

Movies	D1		D2		D3		DN		SVM	
Ratings	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
PCA	**0.65**	0.463	0.681	**0.475**	0.684	**0.486**	0.744	0.408	0.771	0.58
AWV	0.601	0.423	0.618	0.433	0.596	0.448	0.736	0.372	0.73	0.532
MDS	0.592	0.437	0.635	0.449	0.631	0.452	**0.752**	**0.412**	0.773	**0.589**
PPMI	0.583	0.47	0.635	0.453	0.605	0.453	0.73	0.384	**0.825**	0.536
Topic	0.575	**0.473**	**0.789**	0.243	**0.789**	0.38	0.739	0.375	0.704	0.501

3.3.5 Semantic Spaces

In this section, we explain how we obtained four different Semantic Spaces.

3.3.6 Word Directions

For all trees we use grid search to find the best values for the criterion, either the gini score or the information entropy score, the maximum amount of features between [None, 'auto', 'log2'], and additionally, we include whether or not to balance the classes in the grid search.

These single directions typically overfit.

Newsgroups	D1				D2				D3			
	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec
PCA 200	0.955	0.348	0.521	0.261	0.959	0.424	0.678	0.309	0.96	0.454	0.674	0.343
PCA 100	0.957	0.382	0.491	0.313	0.961	0.474	0.679	0.364	**0.963**	0.512	0.694	0.406
PCA 50	0.957	0.373	0.417	0.337	**0.963**	0.478	0.621	0.388	0.963	0.506	0.7	0.396
AWV 200	0.832	0.35	0.226	0.777	0.957	0.383	0.517	0.305	0.958	0.445	0.598	0.354
AWV 100	0.83	0.343	0.219	0.785	0.823	0.36	0.233	**0.792**	0.956	0.387	0.563	0.295
AWV 50	0.807	0.341	0.215	0.816	0.833	0.361	0.236	0.762	0.954	0.392	0.511	0.318
MDS 200	**0.959**	**0.418**	**0.543**	0.339	0.962	0.465	0.669	0.357	0.962	0.493	**0.707**	0.379
MDS 100	0.857	0.365	0.244	0.725	0.959	0.428	0.624	0.326	0.96	0.453	0.644	0.349
MDS 50	0.821	0.324	0.206	0.762	0.842	0.386	0.258	0.77	0.957	0.398	0.596	0.299
D2V 200	0.831	0.343	0.22	0.784	0.96	0.47	**0.683**	0.358	0.962	0.494	0.69	0.385
D2V 100	0.844	0.374	0.243	0.803	0.961	**0.49**	0.642	0.396	0.962	0.517	0.67	0.421
D2V 50	0.845	0.388	0.252	**0.844**	0.962	0.488	0.639	0.395	0.963	**0.537**	0.673	**0.446**

Table 3.5: Newsgroups single dirs

Newsgroups	D1				D2				D3			
	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec	ACC	F1	Prec	Rec
PCA 200	0.955	0.348	0.521	*0.261*	0.959	0.424	0.678	0.309	0.96	0.454	0.674	0.343
PCA 100	0.957	0.382	0.491	0.313	0.961	0.474	0.679	0.364	**0.963**	0.512	0.694	0.406
PCA 50	0.957	0.373	0.417	0.337	**0.963**	0.478	0.621	0.388	0.963	0.506	0.7	0.396
AWV 200	0.832	0.35	0.226	0.777	0.957	0.383	0.517	*0.305*	0.958	0.445	0.598	0.354
AWV 100	0.83	0.343	0.219	0.785	*0.823*	*0.36*	*0.233*	**0.792**	0.956	*0.387*	0.563	*0.295*
AWV 50	*0.807*	0.341	0.215	0.816	0.833	0.361	0.236	0.762	*0.954*	0.392	*0.511*	0.318
MDS 200	**0.959**	**0.418**	**0.543**	0.339	0.962	0.465	0.669	0.357	0.962	0.493	**0.707**	0.379
MDS 100	0.857	0.365	0.244	0.725	0.959	0.428	0.624	0.326	0.96	0.453	0.644	0.349
MDS 50	0.821	*0.324*	*0.206*	0.762	0.842	0.386	0.258	0.77	0.957	0.398	0.596	0.299
D2V 200	0.831	0.343	0.22	0.784	0.96	0.47	**0.683**	0.358	0.962	0.494	0.69	0.385
D2V 100	0.844	0.374	0.243	0.803	0.961	**0.49**	0.642	0.396	0.962	0.517	0.67	0.421
D2V 50	0.845	0.388	0.252	**0.844**	0.962	0.488	0.639	0.395	0.963	**0.537**	0.673	**0.446**

Reuters	D1		D2		D3		Sentiment	D1		D2		D3	
	ACC	F1	ACC	F1	ACC	F1		ACC	F1	ACC	F1	ACC	F1
PCA	0.976	0.658	*0.979*	0.679	*0.977*	*0.467*	PCA	0.739	0.759	**0.797**	**0.814**	0.802	0.805
AWV	*0.975*	0.598	0.979	*0.656*	0.98	0.66	AWV	*0.7*	*0.699*	*0.711*	*0.736*	*0.723*	*0.735*
MDS	0.975	**0.678**	**0.98**	**0.706**	**0.982**	**0.72**	D2V	**0.776**	**0.784**	0.782	0.801	**0.822**	**0.821**
D2V	**0.977**	*0.583*	0.979	0.664	0.98	0.632							
Placetypes	D1		D2		D3		Movies	D1		D2		D3	
OpenCYC	ACC	F1	ACC	F1	ACC	F1	Genres	ACC	F1	ACC	F1	ACC	F1
PCA	*0.632*	*0.371*	*0.704*	*0.381*	*0.735*	0.365	PCA	0.824	*0.412*	*0.82*	0.441	0.913	0.463

3.3.7 Clustered Directions

Newsgroups	D1				D2				D3			
K-means 200	**0.852**	**0.394**	**0.261**	0.795	**0.958**	**0.433**	**0.58**	0.345	**0.963**	**0.513**	**0.704**	0.403
K-means 100	0.842	0.388	0.257	0.791	0.958	0.366	0.516	0.284	0.962	0.5	0.635	**0.412**
K-means 50	0.834	0.381	0.248	**0.819**	0.815	0.336	0.212	**0.81**	0.961	0.485	0.612	0.402
Derrac 200	0.803	0.313	0.202	0.693	0.797	0.306	0.191	0.781	0.958	0.409	0.605	0.309
Derrac 100	0.792	0.305	0.197	0.667	0.791	0.287	0.179	0.721	0.957	0.374	0.56	0.281
Derrac 50	0.769	0.26	0.162	0.661	0.768	0.237	0.143	0.693	0.955	0.315	0.47	0.237

Reuters	D1		D2		D3		Sentiment	D1		D2		D3	
	ACC	F1	ACC	F1	ACC	F1		ACC	F1	ACC	F1	ACC	F1
K-means	**0.875**	**0.338**	**0.975**	**0.54**	0.973	**0.58**	K-means	0.623	0.674	**0.837**	**0.844**	0.658	0.707
Derrac	0.797	0.291	0.973	0.402	**0.974**	0.485	Derrac	**0.712**	**0.735**	0.802	0.82	**0.803**	**0.813**

Placetypes	D1		D2		D3		Movies	D1		D2		D3	
OpenCYC	ACC	F1	ACC	F1	ACC	F1	Genres	ACC	F1	ACC	F1	ACC	F1
K-means	**0.641**	**0.413**	**0.735**	**0.405**	0.75	**0.43**	K-means	**0.813**	**0.431**	**0.913**	**0.513**	**0.913**	**0.506**
Derrac	0.605	0.39	0.672	0.392	**0.755**	0.391	Derrac	0.759	0.341	0.789	0.431	0.911	0.432

Foursquare	ACC	F1	ACC	F1	ACC	F1	Keywords	ACC	F1	ACC	F1	ACC	F1
K-means	**0.913**	**0.462**	**0.911**	**0.5**	**0.891**	**0.511**	K-means	0.667	0.208	0.648	0.202	0.678	0.213
Derrac	0.768	0.392	0.835	0.445	0.805	0.425	Derrac	**0.726**	**0.215**	**0.745**	**0.22**	**0.707**	**0.219**

Geonames	ACC	F1	ACC	F1	ACC	F1	Ratings	ACC	F1	ACC	F1	ACC	F1
K-means	**0.772**	0.43	**0.774**	0.407	**0.819**	**0.472**	K-means	**0.671**	**0.504**	0.638	**0.507**	**0.686**	**0.513**
Derrac	0.678	**0.449**	0.74	**0.411**	0.807	0.415	Derrac	0.651	0.445	**0.669**	0.463	0.627	0.479

Table 3.7: All clustering results

3.4 Qualitative Results

Make reference to the qualitative results found in the previous work here.

3.4.1 Examining the differences between directions

Investigating three potential hypothesis: 1. The ranks are more accurate, so the key directions are better represented that would contribute 2. The spaces/score-types contain unique directions that contribute to the tree directly 3. The spaces/score-types influence the rankings so that they are better represented, but are not directly used in the tree

First, we look at the best scoring directions. Then, we look at the unique directions for each space-type and score-type. The section is then followed by conclusions, and we begin to look into the clusters.

3.4.2 The best-performing directions for each space type

What are the domains that best convey the similarities and differences between different domains?

1. Find domains that act differently (perhaps one domain where a space-type that is not usually scoring high is scoring high, big differences in F1) 2. Get interesting directions from those domains

Movies *(50 MDS NDCG)*	**Sentiment** *(100 D2V NDCG)*	**Newsgroups** *(50 D2V NDCG)*	**Place-types** *(50 PCA Kappa)*	**Reuters** *(200 MDS NDCG)*
horror (scares, scary)	glenda (glen, matthau)	karabag (iranian, turkiye)	blackcountry (listed, westmidlands)	franklin (fund, mthly)
hilarious (funniest, hilarity)	scarlett (gable, dalton)	leftover (flaming, vancouver)	ears (stare, adorable)	quarterly (shearson, basis)
bollywood (hindi, india)	giallo (argento, fulci)	wk (5173552178, 18084tmibmclmsuedu)	spagna (espanha, colores)	feb (28, splits)
laughs (funnier, funniest)	bourne (damon, cusack)	1069 (mlud, wibbled)	oldfashioned (winery, antiques)	22 (booked, hong)
jokes (gags, laughs)	piper (omen, knightley)	providence (norris, ahl)	gardening (greenhouse, petals)	april (monthly, average)
comedies (comedic, laughs)	casper (dolph, damme)	celestial (interplanetary, bible)	pagoda (hindu, carved)	sets (principally, precious)
hindi (bollywood, india)	norris (chuck, rangers)	mlud (wibbled, 1069)	artificial (saturation, cs4)	16 (creditor, trillion)
war (military, army)	holmes (sherlock, rathbone)	endif (olwm, ciphertext)	inner (curved, rooftops)	1st (qtr, pennsylvania)
western (outlaw, unforgiven)	rourke (mickey, walken)	gd3004 (35894, intergraph)	celebrate (festive, celebrity)	26 (approve, inadequate)
romantic (romance, chemistry)	ustinov (warden, cassavetes)	rtfmmitedu (newsanswers, ieee)	vietnamese (ethnic, hindu)	23 (offsetting, weekly)
songs (song, tunes)	scooby (doo, garfield)	eng (padres, makefile)	cn (elevated, amtrak)	prior (recapitalization, payment)
sci (science, outer)	doo (scooby, garfield)	pizza (bait, wiretap)	mannequin (bags, jewelry)	avg (shrs, shr)
funniest (hilarious, funnier)	heston (charlton, palance)	porsche (nanao, mercedes)	falcon (r, 22)	june (july, venice)
noir (noirs, bogart)	homer (pacino, macy)	gebcadredslpittedu (n3jxp, skepticism)	jewish (monuments, cobblestone)	march (31, day)
documentary (documentaries, footage)	welles (orson, kane)	scsi2 (scsi, cooling)	canon60d (kitlens, 600d)	regular (diesel, petrol)
animation (animated, animators)	frost (snowman, damme)	playback (quicktime, xmotif)	reflective (curved, cropped)	4th (qtr, fourth)
adults (adult, children)	streisand (bridget, salman)	35894 (gd3004, medin)	mason (edward, will)	27 (chemlawn, theyre)
creepy (spooky, scary)	davies (rhys, marion)	diesel (volvo, shotguns)	aerialview (manmade, largest)	14 (borrowing, borrowings)
gay (gays, homosexuality)	cinderella (fairy, stepmother)	evolutionary (shifting, hulk)	shelf (rack, boxes)	11 (chapter, ranged)
workout (intermediate, instruction)	boll (uwe, belushi)	techniciandr (obp, 144k)	monroe (raleigh, jefferson)	may (probably, however)
thriller (thrillers, suspense)	rochester (eyre, dalton)	8177 (obp, 144k)	litter (fujichrome, e6)	38 (33, strong)
funnier (laughs, funniest)	edie (soprano, vertigo)	shaw (medicine, ottoman)	streetlights (streetlamp, headlights)	m1 (m2, m3)
suspense (suspenseful, thrillers)	scarecrow (zombies, reese)	scorer (gilmour, lindros)	carlzeiss (f2, voigtlander)	dlr (writedown, debt)
arts (hong, chan)	kramer (streep, meryl)	xwd (xloadimage, openwindows)	manmade (aerialview, below)	five (years, jones)
christianity (religious, religion)	marty (amitabh, goldie)	ee (275, xloadimage)	demolished (neglected, rundown)	bushels (soybeans, ccc)
musical (singing, sing)	columbo (falk, garfield)	com2 (com1, v32bis)	wald (berge, wildflower)	revs (net, 3for2)
gore (gory, blood)	kidman (nicole, jude)	examiner (corpses, brass)	arquitetura (exposition, cidade)	29 (175, include)
animated (animation, cartoon)	juliet (romeo, troma)	migraine (ama, placebo)	greyscale (highcontrast, monochromatic)	acquisition (make, usairs)
gags (jokes, slapstick)	garland (judy, lily)	parliament (parliamentary, armored)	alameda (monday, marin)	payable (div, close)

Table 3.8: Table

3.4.3 How Domain Directions Differ

For the single directions, arrange them by score where the highest scoring directions are at the top. For the clusters, there is no convenient way to organize them without bias, so clusters that are interesting are selected.

Score Types

There are unique directions for each different space type, each suitable to different tasks. NDCG was selected as the best score-type for Sentiment, Newsgroups, Reuters, Movies Genres, Movies Keywords in depth-3 Decision Trees. Place-types foursquare used F1-score, but the classes are very unbalanced and there are few documents.

NDCG	F1	Accuracy	Kappa	Common
gay *(homosexuality, sexuality)*	company *(sell, pay)*	kennedy *(republic, elected)*	definately *(alot, awesome)*	horror *(scares, scares)*
arts *(hong, chan)*	street *(city, york)*	bags *(listened, salvation)*	guns *(gun, shoot)*	laughs *(funnier, funnier)*
sports *(win, players)*	red *(numerous, fashion)*	summers *(verge, medieval)*	flawless *(perfection, brilliantly)*	jokes *(gags, gags)*
apes *(remembered, planet)*	project *(creating, spent)*	revolve *(sincerely, historian)*	mail *(reviewed, rated)*	comedies *(comedic, comedic)*
german *(germans, europe)*	mark *(favor, pull)*	locale *(foster, sharply)*	garbage *(crap, horrible)*	sci *(scifi, alien)*
satire *(parody, parodies)*	lady *(actress, lovely)*	cooler *(downward, reports)*	featurette *(featurettes, extras)*	funniest *(hilarious, hilarious)*
band *(rock, vocals)*	fire *(ground, force)*	spades *(ralph, medieval)*	complaint *(extra, added)*	creepy *(spooky, spooky)*
crude *(offensive, offended)*	post *(essentially, purpose)*	filmography *(ralph, experiments)*	mission *(enemy, saving)*	thriller *(thrillers, thrillers)*
dancing *(dance, dances)*	heads *(large, throw)*	quentin *(downward, anime)*	ruin *(wondering, heck)*	funnier *(laughs, laughs)*
restored *(print, remastered)*	water *(land, large)*	employers *(finishes, downward)*	wars *(forces, enemy)*	suspense *(suspenseful, suspenseful)*
drugs *(drug, abuse)*	road *(drive, trip)*	formal *(victory, kennedy)*	prefer *(compare, added)*	gore *(gory, gory)*
church *(religious, jesus)*	brother *(son, dad)*	tube *(esta, muscle)*	heroes *(packed, hero)*	gags *(jokes, jokes)*
sexuality *(sexual, sexually)*	party *(decide, hot)*	woefully *(restless, knockout)*	necessarily *(offer, draw)*	science *(sci, sci)*
sexually *(sexual, sexuality)*	badly *(awful, poorly)*	scientists *(hilarity, locale)*	portray *(portrayed, portraying)*	gory *(gore, gore)*
england *(british, english)*	limited *(aspect, unlike)*	overboard *(civilized, cinderella)*	critic *(reviewed, net)*	government *(political, political)*
ocean *(sea, boat)*	impression *(instance, reasons)*	rumors *(homosexuality, characteristics)*	reviewed *(rated, mail)*	suspenseful *(suspense, suspense)*
marry *(married, marriage)*	trip *(journey, road)*	salvation *(bags, cooler)*	saving *(carry, forced)*	frightening *(terrifying, terrifying)*
campy *(cult, cheesy)*	michael *(producers, david)*	actively *(assassination, overcoming)*	technical *(digital, presentation)*	military *(army, army)*
christian *(religious, jesus)*	memory *(forgotten, memories)*	stretching *(victory, hideous)*	statement *(exist, critical)*	slapstick *(gags, gags)*
melodrama *(dramatic, tragedy)*	james *(robert, michael)*	downward *(cooler, crawling)*	shocked *(hate, warning)*	scary *(scare, scare)*
sing *(singing, sings)*	thin *(barely, flat)*	rocked *(staple, demented)*	flying *(air, force)*	blu *(unanswered, ray)*
sentimental *(touching, sappy)*	pre *(popular, include)*	affectionate *(esta, muscle)*	danger *(dangerous, edge)*	internetreviews *(rhodes, rhodes)*
depressing *(bleak, suffering)*	faces *(constant, unlike)*	protest *(protective, assassination)*		cgi *(computer, computer)*
evidence *(investigation, accused)*	values *(exception, wise)*	confined *(cooler, downward)*		email *(web, web)*
adorable *(cute, sweet)*	unusual *(odd, seemingly)*	inhabit *(quentin, drawback)*		thrilling *(thrill, exciting)*
episodes *(episode, television)*	lovers *(lover, lovely)*	latin *(communities, mount)*		web *(email, email)*
teenager *(teen, teenage)*	frame *(image, effect)*	reception *(como, finishes)*		horror *(scares, scares)*
magical *(fantasy, lovely)*	mans *(ultimate, sees)*	uptight *(suspensful, stalked)*		laughs *(funnier, funnier)*
health *(medical, suffering)*	efforts *(generally, nonetheless)*	brink *(inexplicable, freddy)*		suspense *(suspenseful, suspenseful)*

Table 3.9: Different score types

Comparing Space Types

We begin by selecting the space that performed well on the genres task for the movies, with the understanding that genres as a key natural classification task will likely make use of good directions that correspond to domain knowledge. After selecting this space, we choose similarly sized spaces from the other space-types, in this case we selected the 200 dimensional MDS space as it performed the best and from there, we selected the 200 dimensional PCA space and AWV space. We also use the same score-type and frequency cut-off as the best performing space-type. In this case, the best performing type for the PCA space was 20000 frequency cutoff and NDCG, and we are comparing to 10000 frequency cutoff. This means that we are sometimes using a slightly worse performing space-type than the one we used as our final results, and that the original space has a performance advantage, but we have chosen to do so to make the results more consistent and specific. We approach these qualitative experiments with the following idea: spaces that perform better on natural domain tasks using decision trees contain unique natural directions that other spaces do not have.

The commonalities between spaces are much more prevalent than the differences, with natural concepts of the domain being represented in all of the different space types. However, different spaces do perform better than others on natural domain tasks. In this section, we investigate why this occurs and the differences between spaces built using a standard frequency-based approach, word-vectors and doc2vec, which uses a combination of contextual information and word vectors.

Comparing MDS, AWV and PCA in the Movies domain

MDS	AWV	PCA	Common
berardinelli *(employers, distributor)*	billy *(thrown, dirty)*	amount *(leaving, pick)*	noir *(fatale, femme)*
crawford *(joan, davis)*	brother *(brothers, boys)*	fails *(fit, pick)*	gay *(homosexual, homosexuality)*
hitchcocks *(hitchcock, alfred)*	fonda *(henry, jane)*	pick *(fails, fit)*	prison *(jail, prisoners)*
warners *(warner, bros)*	building *(built, climax)*	stands *(fails, cover)*	arts *(rec, robomod)*
nuclear *(weapons, soviet)*	train *(tracks, thrown)*	surprisingly *(offer, fit)*	allens *(woody, allen)*
joan *(crawford, barbara)*	slaves *(slavery, excuse)*	copyright *(email, compuserve)*	jokes *(laughs, joke)*
kidnapped *(kidnapping, torture)*		length *(reflect, expressed)*	animation *(animated, cartoon)*
hop *(hip, rap)*		profanity *(reflect, producers)*	sherlock *(holmes, detective)*
kung *(martial, jackie)*		compuserve *(copyright, internetreviews)*	western *(westerns, wayne)*
ballet *(dancers, dancer)*		talents *(admit, agree)*	songs *(song, lyrics)*
gambling *(vegas, las)*		admit *(agree, talents)*	comedies *(comedic, laughs)*
alcoholic *(drunk, alcoholism)*		developed *(introduced, sounds)*	workout *(exercise, challenging)*
waves *(surfing, wave)*		intended *(bother, werent)*	laughs *(funnier, hilarious)*
jaws *(jurassic, godfather)*		constantly *(putting, sounds)*	drug *(drugs, addict)*
jungle *(natives, island)*		tired *(anymore, mediocre)*	sci *(science, fiction)*
employers *(berardinelli, distributor)*		produced *(spoiler, surprising)*	documentary *(documentaries, interviews)*
pot *(weed, stoned)*		involving *(believes, belief)*	students *(student, schools)*
canadian *(invasion, cheap)*		anymore *(continue, tired)*	thriller *(thrillers, suspense)*
murphy *(eddie, comedian)*		leaving *(fit, pick)*	allen *(woody, allens)*
comics *(comedian, comedians)*		makers *(producers, aspects)*	funniest *(hilarious, laughing)*
kidnapping *(kidnapped, torture)*		introduced *(developed, considered)*	gags *(jokes, slapstick)*
subscribe *(email, internetreviews)*		loses *(climax, suffers)*	adults *(children, adult)*
vegas *(las, gambling)*		negative *(positive, bother)*	animated *(animation, cartoon)*
distributor *(berardinelli, employers)*		expressed *(reflect, opinions)*	dancing *(dance, dances)*
wave *(waves, surfing)*		mildly *(mediocre, forgettable)*	teen *(teenage, teens)*
rhodes *(internetreviews, email)*		helped *(putting, allowed)*	soldiers *(soldier, army)*
hippie *(pot, sixties)*		reflect *(expressed, opinions)*	indie *(independent, festival)*
weed *(pot, stoned)*		opinions *(reflect, expressed)*	suspense *(suspenseful, thriller)*
caribbean *(pirates, island)*		frequently *(occasionally, consistently)*	creepy *(scary, eerie)*
eddie *(murphy, comedian)*		content *(agree, proves)*	italian *(italy, spaghetti)*
sixties *(beatles, hippie)*		allowed *(helped, werent)*	jews *(jewish, nazis)*
... 8 More		suffers *(lacks, loses)*	... 1480 more

Table 3.10: ok dude

Comparing PPMI representations to doc2vec

3.4.4 What is the value of different score-types?

3.4.5 Producing Semantic Spaces

We use unsupervised representation learning methods, with the intention to obtain a representation that represents all salient features of the domain and can adapt to a variety of tasks.

For the semantic space, we compute the Positive Pointwise Mutual Information (See **??**) scores for the Bag-Of-Words, and use that as input to a variety of different off-the-shelf dimensionality reduction algorithms. We explain these in further detail in Section **??**.

3.4.6 Quantitative Results

From a domain, e.g. movie reviews, where each document is a collection of reviews for a movie, we preprocess the text such that it is converted to lower-case, and non-alphanumeric characters are removed. From here, we remove standard English stop words using the NLTK library [**?**]. We show an example of a review's original and converted formats in Figure **??**. From this preprocessed corpus, we obtain a Bag-Of-Words where we count the frequency of each term $BOW_w f$, see 2.1.1.

The difference between single directions and clusters is best highlighted when comparing their use in simple interpretable classifiers. In figure **??** we demonstrate this.

1. Negative directions (e.g. church for horror) 2. Non-contextualized, non-direct ways of classifying, versus clustering which finds salient properties which almost directly correspond to these natural tasks.

3.4.7 Interpretability Results

D2V	**MDS**	**Common**
leftover (pizza, brake)	hi (folks, everyone)	chastity (shameful, soon)
wk (5173552178, 18084tmibmclmsuedu)	looking (spend, rather)	n3jxp (gordon, gebcadredslpittedu)
eng (padres, makefile)	need (needs, means)	skepticism (gebcadredslpittedu, n3jxp)
porsche (nanao, 1280x1024)	post (summary, net)	anyone (knows, else)
diesel (cylinders, steam)	find (couldnt, look)	gebcadredslpittedu (soon, gordon)
scorer (gilmour, lindros)	hello (kind, thank)	intellect (soon, gordon)
parliament (caucasus, semifinals)	david (yet, man)	please (respond, reply)
atm (padres, inflatable)	got (mine, youve)	thanks (responses, advance)
cryptology (attendees, bait)	go (take, lets)	email (via, address)
intake (calcium, mellon)	question (answer, answered)	know (let, far)
433 (366, 313)	interested (including, products)	get (wait, trying)
ghetto (warsaw, gaza)	list (mailing, send)	think (important, level)
lens (lenses, ankara)	sorry (guess, hear)	good (luck, bad)
rushdie (sinless, wiretaps)	heard (ever, anything)	shafer (dryden, nasa)
immaculate (porsche, alice)	cheers (kent, instead)	bobbeviceicotekcom (manhattan, beauchaine)
keenan (lindros, bosnian)	say (nothing, anything)	dryden (shafer, nasa)
boxer (jets, hawks)	number (call, numbers)	im (sure, working)
linden (mogilny, 176)	mailing (list, send)	sank (bronx, away)
candida (yeast, noring)	call (number, phone)	banks (soon, gordon)
octopus (web, 347)	thank (thanx, better)	like (sounds, looks)
czech (detectors, kuwait)	read (reading, group)	shameful (soon, gordon)
survivor (warsaw, croats)	phone (company, number)	could (away, bobbeviceicotekcom)
5173552178 (circumference, wk)	mail (send, list)	would (appreciate, wouldnt)
18084tmibmclmsuedu (circumference, wk)	doesnt (isnt, mean)	beauchaine (bobbeviceicotekcom, away)
3369591 (circumference, wk)	lot (big, little)	ive (seen, never)
mcwilliams (circumference, wk)	thats (unless, youre)	surrender (soon, gebcadredslpittedu)
coldblooded (dictatorship, czech)	believe (actually, truth)	problem (problems, fix)
militia (federalist, occupying)	youre (unless, theyre)	windows (31, dos)
cbc (ahl, somalia)	send (mail, mailing)	gordon (soon, gebcadredslpittedu)

Table 3.11: Comparing an MDS sapce to a D2V space for Newsgroups, where a D2V space performed best..

Chapter 4

Fine-tuning Vector Spaces to Improve Their Directions

"Commonly, these representations are made in a single vector space with similarity being the main structure of interest. However, recent work by Mikolov et al. (2013b) on a word-analogy task suggests that such spaces may have further use- ful internal regularities. They found that seman- tic differences, such as between big and small, and also syntactic differences, as between big and bigger, were encoded consistently across their space. In particular, they solved the word-analogy problems by exploiting the fact that equivalent re- lations tended to correspond to parallel vector- differences. [3]

[3] "Explicitly designing such structure into a neural network model results in rep- resentations that decompose into orthog- onal semantic and syntactic subspaces. We demonstrate that using word-order and morphological structure within En- glish Wikipedia text to enable this decomposition can produce substantial im- provements on semantic-similarity, pos- induction and word-analogy tasks."

This means that despite state-of-the-art results in Natural Language Processing tasks like Language Modelling, Machine Translation, Text Classification, Natural Language Inference, Abstractive Summarization, and Dependency Parsing being dominated by neural networks that learn and improve these kind-of representations, it is not clear what information has been represented.

4.1 Experiments

We find that non-linearity is useful.

Chapter 5

Investigating Neural Networks In Terms Of Directions

5.1 Appendix

5.1.1 Chapter 3 Space Types

	Genres			Keywords			Ratings		
Movies	D1	D2	D3	D1	D2	D3	D1	D2	D3
Space	50 PCA	50 MDS	100 MDS	200 PCA	200 MDS	200 MDS	50 PCA	200 PCA	50 PCA
Single directions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Newsgroups			Sentiment			Reuters		
Rep	200 PCA	200 PCA	100 PCA	PCA 100	PCA 50	PCA 50	200 PCA	200 PCA	100 PCA
Single dir	200 MDS	100 D2V	50 D2V	D2V 100	PCA 50	D2V 100	N/A	N/A	N/A
	Foursquare			OpenCYC			Geonames		
Placetypes	D1	D2	D3	D1	D2	D3	D1	D2	D3
Rep	MDS 100	AWV 50	MDS 200	AWV 50	MDS 200	AWV 50	MDS 50	MDS 50	AWV 200
Single dir	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table 5.1: Space-types, clusters have the same as single directions.

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