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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

|                                |             |
|--------------------------------|-------------|
| <b>Abstract</b>                | <b>iv</b>   |
| <b>Acknowledgements</b>        | <b>v</b>    |
| <b>Contents</b>                | <b>vi</b>   |
| <b>List of Publications</b>    | <b>ix</b>   |
| <b>List of Figures</b>         | <b>x</b>    |
| <b>List of Tables</b>          | <b>xi</b>   |
| <b>List of Algorithms</b>      | <b>xii</b>  |
| <b>List of Acronyms</b>        | <b>xiii</b> |
| <b>1 Introduction</b>          | <b>1</b>    |
| 1.1 Motivation . . . . .       | 1           |
| 1.1.1 Directions . . . . .     | 3           |
| 1.2 Interpretability . . . . . | 4           |

---

|          |  |          |
|----------|--|----------|
| 1.3      | Thesis Overview / Contributions . . . . .                          | 5        |
| <b>2</b> | <b>Background</b>  | <b>6</b> |
| 2.1      | Text . . . . .   | 6        |
| 2.1.1    | Bag-of-words . . . . .   | 6        |
| 2.2      | Text classification . . . . .                                      | 6        |
| 2.2.1    | Decision Trees . . . . .   | 6        |
| 2.2.2    | Support Vector Machines . . . . .                                  | 6        |
| 2.2.3    | Neural Networks . . . . .  | 7        |
| 2.2.4    | Vector Spaces . . . . .  | 7        |
| 2.2.5    | Word Representations . . . . .                                     | 7        |
| 2.2.6    | Document Representations . . . . .                                 | 7        |
| 2.3      | Interpretable Representations . . . . .                            | 7        |
| <b>3</b> | <b>Converting Vector Spaces into Interpretable Representations</b> | <b>9</b> |
| 3.1      | Introduction . . . . .   | 9        |
| 3.2      | Related Work . . . . .   | 14       |
| 3.2.1    | Interpretable Representations . . . . .                            | 15       |
| 3.2.2    | Interpretable Classifiers . . . . .                                | 15       |
| 3.3      | Method . . . . .   | 15       |
| 3.3.1    | Quantitative Results . . . . .                                     | 20       |
| 3.3.2    | Interpretability Results . . . . .                                 | 22       |



|          |  |           |
|----------|--|-----------|
| <b>4</b> | <b>Fine-tuning Vector Spaces to Improve Their Directions</b> | <b>23</b> |
| 4.1      | Experiments . . . . .  | 23        |
| <b>5</b> | <b>Investigating Neural Networks In Terms Of Directions</b>  | <b>24</b> |
|          | <b>GNU Free Documentation License</b>                        | <b>25</b> |
|          | <b>Bibliography</b>  | <b>34</b> |

## List of Publications

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

- 
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# List of Figures

|     |  |    |
|-----|--|----|
| 1.1 | Bag-of-words . . . . .   | 2  |
| 1.2 | Example properties . . . . .   | 2  |
| 3.1 | A conceptual space of movies, where regions correspond to properties and entities are points. . . . .  | 12 |
| 3.2 | This figure shows a 2d toy space where entities are shapes and directions are properties. We demonstrate on the right the method to induce a ranking from the directions, in particular by using the dot-product of the entity point on the directions vector. In the same way for a more complex space, we can understand each entity point to be ranked on thousands of property directions, and the space to be much higher dimensionality. . . . . | 13 |
| 3.3 | 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. . . . .  | 14 |
| 3.4 | A conceptual space of movies, where regions correspond to properties and entities are points. . . . .  | 21 |

## List of Tables

|     |  |    |
|-----|--|----|
| 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. . . . . | 21 |
| 3.2 | Results for 20 newsgroups. . . . .   | 22 |

# List of Algorithms

# List of Acronyms

**ML** Machine Learning

**NLP** Natural Language Processing

**NDCG** Normalized Discounted Cumulative Gain

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# 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

| <u>Entity: X</u> |                  | <u>Entity: Y</u> |                  | <u>Entity: Z</u> |                  |
|------------------|------------------|------------------|------------------|------------------|------------------|
| <u>Word</u>      | <u>Frequency</u> | <u>Word</u>      | <u>Frequency</u> | <u>Word</u>      | <u>Frequency</u> |
| Dog              | 51               | Dog              | 51               | Dog              | 51               |
| Cat              | 40               | Cat              | 40               | Cat              | 40               |
| Man              | 11               | Man              | 11               | Man              | 11               |
| Cheese           | 0                | Cheese           | 0                | Cheese           | 0                |
| Dog              | 51               | Dog              | 51               | Dog              | 51               |
| Cat              | 40               | Cat              | 40               | Cat              | 40               |
| Man              | 11               | Man              | 11               | Man              | 11               |
| Cheese           | 0                | Cheese           | 0                | Cheese           | 0                |

Figure 1.1: Bag-of-words

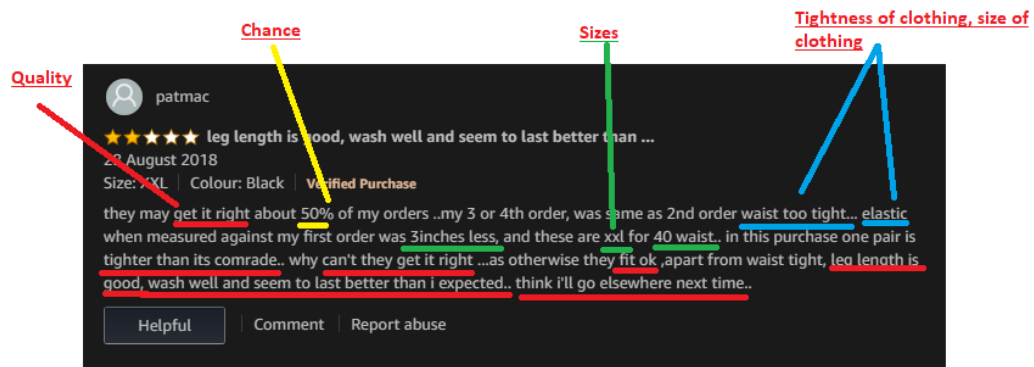


Figure 1.2: Example properties

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 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' [12] also has many positive effects for its users, like lower response times [11, 8], better question answering and confidence for logical problem questions [8] and higher satisfaction [11].
- Transparency:
- 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 [5]: 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.

# Background

## 2.1 Text

### 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 lowercase 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

### **2.2.2 Support Vector Machines**

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

### **2.2.3 Neural Networks**

- Difference between SVM and Nnet

### **2.2.4 Vector Spaces**

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

### **2.2.5 Word Representations**

- Word-vectors

### **2.2.6 Document Representations**

**Conceptual spaces**

- 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.

# Converting Vector Spaces into Interpretable Representations

## 3.1 Introduction

A "direction" refers in this case to the orthogonal direction to a hyper plane that separates a term in a vector space. As the hyper plane separates entities, this means that the entities furthest along the hyper plane, at the end classified positively, are the entities we are most sure have the term we found the hyper plane for. To see an example of this, see ?? With this understanding, it becomes possible to induce a ranking of entities on the properties by finding the dot product of the entity points on the direction vector.

Topic models such as Latent Dirichlet Allocation (LDA) represent documents as multinomial distributions over latent topics, where each of these topics corresponds to a multinomial distribution over words [1]. These topics tend to correspond to semantically meaningful concepts, hence topic models tend to be rather interpretable [4]. To characterize the semantic concepts associated with the learned topics, topics are typically labelled with the most probable words according to the corresponding distribution.

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 Our method can use any vector space that linearly separates entities, and so it has potential longevity. This means that our method is relying on structure in the space that does not directly correspond to our desired representation - we can view our approach as a linear transformation of the space. We address this problem in Chapter ???. However, we have the capability to leverage many different methods to construct a vector space for our representation, so as long as dense representations of entities exist it will be possible to use our method, and as they are improved the results that our method can achieve will be improved too. This kind of flexibility also gives us the potential to combine the resultant representations from different vector spaces for classification, e.g. concatenating the vectors from different spaces.

The success of these semantic spaces similarity-based structure has lead many to investigate how to obtain formal relationships from them. One such striking example is in that of linear analogies in word-vectors (see Section ??, where it was found that the vector XXXX[King queen blah blah]XXXXXXXX, formally justified in [?]. These relationships have been expanded on, for example [13] found that "equivalent relations tended to correspond to parallel vector differences" [10], while [10] discovered that by decomposing representations into orthogonal semantic and syntactic subspaces they were able to produce substantial improvements on various tasks. Additionally, [?] found that 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.

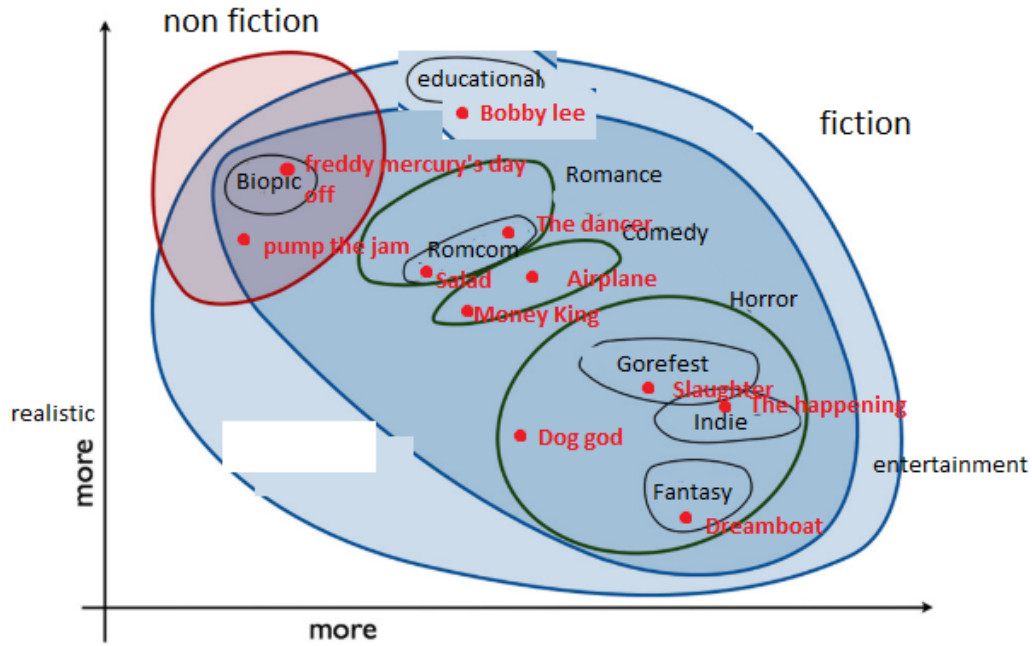
This brings up an essential point: When using a semantic space, are we taking advantage of relationships that are discriminative or incorrect? The danger of relying on these spaces and the models that use them has greatly affected their adoption in critical application areas like medicine, and has raised legal concerns about their application in e.g. determining if someone is suitable for a loan.

Distributional representations like vector spaces have the ability to represent semantic information spatially. Vector spaces built from a domain-specific corpus of text that represent this kind of information, also known as 'semantic spaces', are used, for instance, One way to understand how a semantic space represents information is as a conceptual space [7]. In this space, we can understand domain entities, e.g. movies in a domain of IMDB movie reviews, to be represented as points, and domain properties to be in regions around these points. In figure 3.1, we show an example conceptual space for movies.

The semantic relation that we focus in on this paper are directions that correspond to salient features from the considered domain.

These kind-of directions have been used in many different ways for different domains, For instance, [?] found that features of countries, such as their GDP, fertility rate or even level of CO<sub>2</sub> 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.

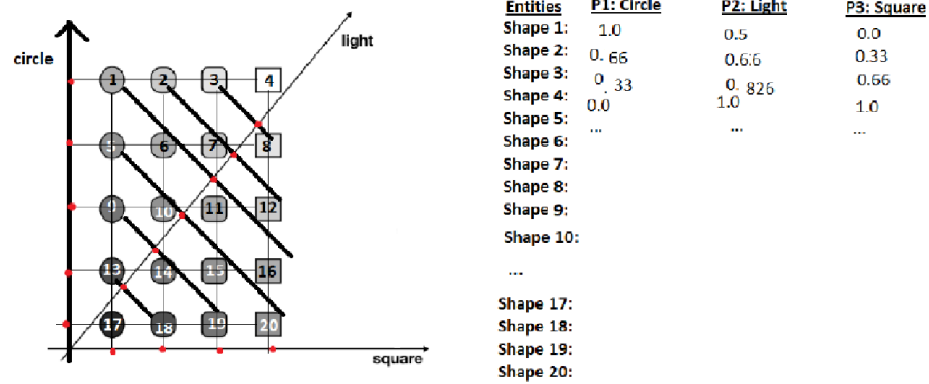
By finding the dot product between entity points in the space and direction vectors, it is possible to induce a ranking of entities on those directions. In this chapter, we more deeply investigate the potential of direction vectors to rank entities on properties to form an interpretable representation.



**Figure 3.1: A conceptual space of movies, where regions correspond to properties and entities are points..**

In this thesis, we refer to these direction vectors as directions to convey the ordinal meaning, and directions as 'properties' if they are sufficiently salient in the space, e.g. In a domain of IMDB movie reviews where movies are entities, a direction on the word "The" would not be a property, but a direction on the word "Horror" would be.

We demonstrate the effect of different filtering methods to find properties, the ability of different clustering methods to label properties, as well as the number and types of directions, for use in a low-depth interpretable linear classifier; a Decision Tree. In Figure 3.3, we demonstrate how depth could affect a Decision Tree that uses salient properties. These trees are not only evaluated quantitatively on key domain tasks, we also evaluate how interpretable the resulting rules are. This gives us a comprehensive idea of how we can use these rankings as an interpretable representation. By using a Decision Tree, we can identify salient properties - if we are able to construct a simple but high-scoring classifier for if a movie is a 'Comedy' using only our ranking of

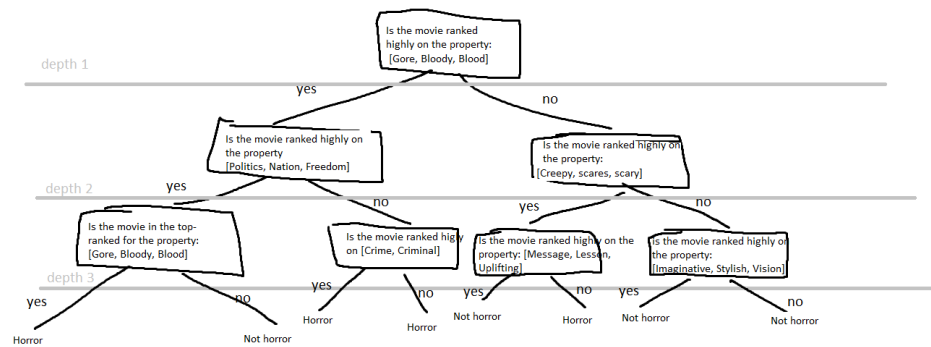


**Figure 3.2:** This figure shows a 2d toy space where entities are shapes and directions are properties. We demonstrate on the right the method to induce a ranking from the directions, in particular by using the dot-product of the entity point on the directions vector. In the same way for a more complex space, we can understand each entity point to be ranked on thousands of property directions, and the space to be much higher dimensionality..

entities on the property  $p = \text{"Funny"}, \text{"Hilarious"}, \text{"Laughing"}$  then we know that this property is salient. Although this is an extreme case, for more complex concepts, if we have salient properties that form the building blocks of this concept, then the model can be less complex and more general, two desirable properties for interpretable classifiers.

In a case study by [14], giving the business users the option between a model with higher classification score but more input variables and a lower classification score but less input variables resulted in more buy-in for system designers. By accurately representing salient concepts in the domain, we are also able to offer a similar option; less nodes in the decision tree in exchange for more accuracy.

This chapter continues as follows: We begin by describing the work related to this , giving valuable context for the utility and potential of our approach. This is followed by an explanation of the method, including the variations we have adopted for our experimental work. We follow this with our qualitative experimentation, explaining



**Figure 3.3:** 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. .

how these variations affect the results, as well as the interpretability of the method, and we end with a quantitative analysis on how well we can represent domain knowledge using decision trees constrained to a limited depth.

## 3.2 Related Work

**Linear Classifiers** Decision trees, linear SVM's, logistic regression, decision tables, IF Then rules.

What are the available options for interpretable linear classification?

How have each of these methods been measured or validated in the literature in regards to interpretability? How about application to real world situations?

**Non linear classifiers** What non linear classifiers networks are interpretable? How have they done it? How have they measured it? How does it compare to a linear method?

*Neural networks* Approximating w/linear model, Interpretable nodes/weights

*Other Stuff*

### 3.2.1 Interpretable Representations

### 3.2.2 Interpretable Classifiers

There are two ways in which topic models can be used for document classification. First, a supervised topic model can be used, in which the underlying graphical model is explicitly extended with a variable that represents the class label [3]. Second, the parameters of the multinomial distribution corresponding to a given document can be used as a feature vector for a standard classifier, such as a Support Vector Machine (SVM) or Decision Tree. LDA has been extended by many approaches, e.g. aiming to avoid the need to manually specify the number of topics [?], modelling correlations between topics [2], or by incorporating meta-data such as authors [?] or time stamps [?].

Broadly speaking, in the context of document classification, the main advantage of topic models is that their topics tend to be easily interpretable, while vector space models tend to be more flexible in the kind of meta-data that can be exploited. The approach we propose in this paper aims to combine the best of both worlds, by providing a way to derive interpretable representations from vector space models.

## 3.3 Method

We begin by describing the process that [5] used to obtain a representation of entities composed of properties. Then, we cover the additional methods we propose to improve this process.

### 3.3.1 Initial Bag-of-Words

In this section, we describe how we go from an unstructured text representation of a domain to an interpretable representation composed of distinct properties.

Our process is generally in three parts, first we obtain directions for terms from the domain  $T_d$  see ??, then we filter these terms to remove those that will not result in good properties. Finally, we cluster the remaining terms to obtain property directions  $P_d$  and an associated label  $l = [t_1, \dots, t_n]$ .

We start with a domain-specific vector space  $S_e$  and its associated bag-of-words (BOW) representation  $B_w$ . To obtain these properties, we use a variant of the unsupervised method proposed in [?], which we explain in this section.

#### Obtaining Term Directions

We can understand that only some words will be properties, as only some correspond to domain knowledge, e.g. in a domain of IMDB movies, the word "the" does not correspond to a property of the domain, but the word "horror" does. Initially, we obtain rankings of entities for each word in the space.

As an initial filtering step, we remove words that do not meet a frequency threshold, with the understanding that words that do not occur in a minimum amount of documents are unlikely to correspond to properties as they are too specific to a subset of movies, which would make them difficult to learn. This leaves us with  $w_n$  words. We show the kind of words that would be poorly represented in ??.

Then, for each considered word  $w$ , a logistic regression classifier is trained to find a hyperplane  $H_w$  in the space that separates entities  $e$  which contain  $w$  in their BOW  $B_e$  representation from those that do not. The vector  $v_w$  perpendicular to this hyperplane is then taken as a direction that models the word  $w$ . In ??, we show an example of this in a toy domain. To rank the objects on the entity, if  $e$  is the representation of an

entity in the given vector space  $S_e$  then we can think of the dot product  $v_w \cdot e$  as the value  $r_e w$  of object  $e$  for vector  $v_w$ , and in particular, we take  $r_{e1} < r_{e2}$  to mean that  $e_2$  has the property labelled with the word  $w$  to a greater extent than  $e_1$ . The result of this is shown in ???. Example entities, with their associated highest and lowest ranking properties, are shown in ???.

### Filtering Directions

With the rankings  $R_r$ , we could create a representation of each entity  $S_e$ , composed of  $w_n$  dimensions, where each dimension is a ranking of the entity  $e$  on that word  $w_r e$ . However, many of the words do not properties. In-order to filter these words out, 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 logistic regression classifier: if this classifier is sufficiently accurate, it must mean that whether word  $w$  relates to object  $o$  (i.e. whether it is used in the description of  $o$ ) is important enough to affect the semantic space representation of  $o$ . In such a case, it seems reasonable to assume that  $w$  describes a salient property for the given domain.

**Cohen’s Kappa.** 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, X proposed to use Cohen’s Kappa score instead. In our experiments, however, we found that accuracy sometimes yields better results, so we keep this 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  $r_e$  of the entity  $e$  are those induced by the dot products  $v_w \cdot e$  and the relevance scores are determined by the Pointwise Positive Mutual Information

(PPMI) score  $ppmi(w, e)$ , of the word  $w$  in the BoW representation of entity  $e$  where  $ppmi(w, e) = \max(0, \log(\frac{p_{we}}{p_{w*} \cdot p_{*e}}))$ , and

$$p_{wo} = \frac{n(w, o)}{\sum_{w'} \sum_{o'} n(w', o')}$$

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

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 properties scored highly for each domain.

### Obtaining Salient Properties

If we consider two directions, "Blood" and "Gore", we can understand both of these to be approximating a property of films; How much blood they contain. Because of this, we can expect their directions to be very similar to each other. Averaging these directions together would result in a direction inbetween them. Similarly, obtaining a hyper plane using a Logistic Regression classifier that uses occurrences of both and either of these terms as positive would be similar to this averaged direction. As 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. This is the principle behind our clustering method - going from term directions to property directiona.

A term direction for "beautiful" is nebulous in the sense that we are not necessarily able to intuit its associated property. However, once we cluster the terms to find the



property ("beautiful", "cinematography" "shots") we are given valuable context for the word. This is another advantage for clustering, we are able to construct a list of terms that label the property, allowing us to more easily understand the meaning of the ranking we induce.

Naturally, it is sometimes not enough to see a list of terms and understand the property without domain knowledge. However, by examining how classifiers use these directions to classify key domain knowledge we are better able to understand what they are modelling. For example, when classifying if a movie is a sci-fi, we see that if a movie is ranked highly on the term "science, scientist", then it is not a sci-fi movie. However, when classifying if a movie is a biography, we see that if a movie is ranked highly on "science, scientist" then it is a biography movie. From this, we can understand that the property is not about mad scientists, but normal non-fiction science.

As this method is sensitive to the first direction selected (if the first direction is not a property then we will likely find a few useless terms before landing on something useful)

Although we are able to find the words that are most salient, the properties in the domain may not correspond directly to words. Further, the properties may not be well described by their associated word. In-order to find better representations of properties, we cluster together similar vectors  $v_w$ , following the assumption that those vectors which are similar are representing some property more general than their individual words, and we can find it between them. As the final step, we cluster the best-scoring candidate feature directions  $v_w$ . Each of these clusters will then define one of the feature directions to be used in applications. The purpose of this clustering step is three-fold: it will ensure that the feature directions are sufficiently different (e.g. in a space of movies there is little point in having *funny* and *hilarious* as separate features), it will make the features easier to interpret (as a cluster of terms is more descriptive than an individual term), and it will alleviate sparsity issues when we want to relate features with the BoW representation, which will play an important role for the fine-

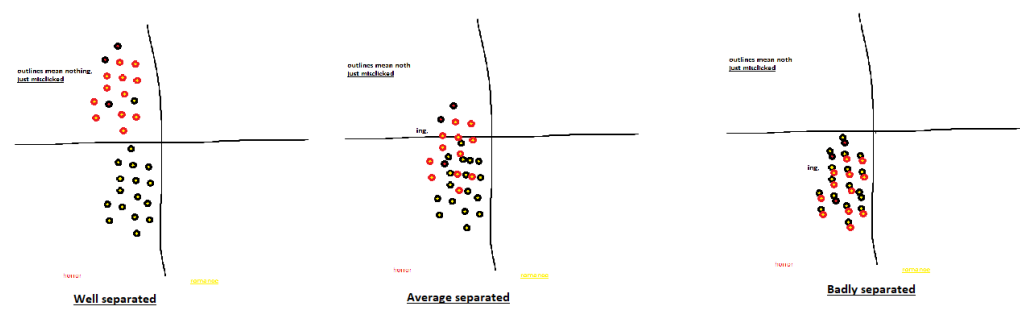
tuning method described in the next section.

As input to the clustering algorithm, we consider the  $N$  best-scoring candidate feature directions  $v_w$ , where  $N$  is a hyperparameter. To cluster these  $N$  vectors, we have followed the approach proposed in [?], which we found to perform slightly better than  $K$ -means. 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. We refer to [?] for more details. The output of this step is a set of clusters  $C_1, \dots, C_K$ , 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  $v_{C_1}, \dots, v_{C_K}$  are the feature directions that are identified by our method.

Table ?? displays some examples of clusters that have been obtained for three of the datasets that will be used in the experiments, modelling respectively movies, place-types and newsgroup postings. For each dataset, we used the scoring function that led to the best performance on development data(see Section ??). Only the first four words whose direction is closest to the centroid  $v_C$  are shown. **K-Means Derrac’s K-Means Variation Mean-shift Hdbscan**

### 3.3.2 Quantitative Results

This section focuses on using linear classifiers to determine how well our method represents domain knowledge compared to standard baselines. We can understand that an accurate representation of domain knowledge will be one that ensures semantically distinct entities are separated, and semantically similar entities are close together. Put another way, if the space is representing domain knowledge well we can expect that the space should be linearly separable for key semantics of the domain. For example, a good vector space in the domain of movies constructed from IMDB movie reviews



**Figure 3.4: A conceptual space of movies, where regions correspond to properties and entities are points..**

|                            | Top PPMI scoring terms   |
|----------------------------|--|
| Example Horror Entity      | 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 |
| Somewhere Inbetween Entity | 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 |
| Similar Romance movie      | 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..**

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 3.4. For a Bag-Of-Words, we can expect similar entities to have similarly scoring terms ??.

When selecting the parameters to use for the doc2vec space when obtaining directions, we choose the one that scored the highest for its class on a Linear SVM, rather than tuning the entire process around the doc2vecs vectors. We use the kind of multi-class strategy as a hyper-parameter for each class-type in the grid search. We test the

|         | SVM          | DT (N)       | DT (3)      | DT (2)       | DT (1)       |
|---------|--------------|--------------|-------------|--------------|--------------|
| PPMI    | 0.594        | <b>0.441</b> | <b>0.44</b> | <b>0.441</b> | <b>0.315</b> |
| PCA 50  | 0.509        | 0.418        | 0.308       | 0.418        | 0.229        |
| PCA 100 | 0.577        | 0.412        | 0.36        | 0.412        | 0.238        |
| PCA 200 | 0.597        | 0.409        | 0.342       | 0.409        | 0.24         |
| D2V 50  | 0.592        | 0.308        | 0.308       | 0.308        | 0.244        |
| D2V 100 | 0.613        | 0.335        | 0.324       | 0.335        | 0.234        |
| D2V 200 | <b>0.619</b> | 0.369        | 0.369       | 0.369        | 0.251        |
| AWV 50  | 0.348        | 0.233        | 0.233       | 0.233        | 0.213        |
| AWV 100 | 0.378        | 0.236        | 0.236       | 0.236        | 0.208        |
| AWV 200 | 0.451        | 0.236        | 0.236       | 0.236        | 0.22         |
| MDS 50  | 0.381        | 0.242        | 0.242       | 0.242        | 0.191        |
| MDS 100 | 0.432        | 0.238        | 0.238       | 0.238        | 0.148        |
| MDS 200 | 0.481        | 0.243        | 0.243       | 0.243        | 0.188        |

**Table 3.2: Results for 20 newsgroups.**

OneVsOne classifier method, treating each as binary problems, the OneVsRest method and the OutputCode method. We are not able to obtain an MDS space for sentiment or doc2vec spaces for placetypes/movies.

As our work performs well even at lower-depth trees, this gives potential users more flexibility in how they want to present the information, e.g. to a potential client. Compared to bag-of-words, which loses its representation capabilities the lower the depth.

### Results for vector spaces and bag-of-words

#### 3.3.3 Interpretability Results

# **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 useful internal regularities. They found that semantic 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 relations tended to correspond to parallel vector-differences. [10]

[10] "Explicitly designing such structure into a neural network model results in representations that decompose into orthogonal semantic and syntactic subspaces. We demonstrate that using word-order and morphological structure within English Wikipedia text to enable this decomposition can produce substantial improvements on semantic-similarity, pos-induction and word-analogy tasks."

## **4.1 Experiments**

We find that non-linearity is useful.

---

## ***Chapter 5***

# **Investigating Neural Networks In Terms Of Directions**

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