Beyond Word Embeddings: Representations for Multi-modal Data

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Abstract

Methods that calculate dense vector representations for text have proven to be very successful for knowledge representation. We study how to estimate dense representations for multi-modal data (e.g., text, continuous, categorical). We propose Feat2Vec as a novel model that supports supervised learning when explicit labels are available, and self-supervised learning when there are no labels. Feat2Vec calculates embeddings for data with multiple feature types enforcing that all embeddings exist in a common space. We believe that we are the first to propose a method for learning self-supervised embeddings that leverage the structure of multiple feature types. Our experiments suggest that Feat2Vec outperforms previously published methods, and that it may be useful for avoiding the cold-start problem.

1 Introduction

Informally, in machine learning a *dense representation*, or *embedding* of a vector $\vec{x} \in \mathbb{R}^n$ is another vector $\vec{\beta} \in \mathbb{R}^r$ that has much lower dimensionality ($r \ll n$) than the original representation. In general, we consider two kind of models that produce embeddings: **(i) supervised methods**, like matrix factorization, calculate embeddings that are highly tuned to a prediction task. For example, in the Nextflix challenge, movie identifiers are embedded to predict user ratings. On the other hand, **(ii) self-supervised methods** (sometimes referred to as unsupervised methods) are not tuned for the prediction task they are ultimately used for. For example, word embedding algorithms such as Word2Vec (Mikolov et al., 2013b) are self-supervised. These algorithms are typically evaluated by analogy solving, or sentiment analysis (Le and Mikolov, 2014), even though their loss functions are not tuned for either of these tasks.

In this paper, we propose Feat2Vec as a novel method that embeds arbitrary feature types, such as text, numerical or categorical data, in a common vector space—for both supervised and self-supervised scenarios. We believe that this is the first self-supervised algorithm that is able to calculate embeddings for multi-modal data, datasets with multiple feature types. Consider the non-trivial work that was required to extend a model like Word2Vec to support additional features. The authors of the seminal Doc2Vec (Le and Mikolov, 2014) paper needed to design both a new neural network and a new sampling strategy to add a single feature (document ID). Feat2Vec is a general method that allows calculating embeddings for any number of features.

2 Feat2Vec

In this section we describe how Feat2Vec learns embeddings of feature groups.

2.1 Model

Feat2Vec predicts a target output $\hat{y}$ from a list of feature groups constructed from a partition $\vec{\boldsymbol{\kappa}}$ of raw features $\vec{\mathbf{x}}$:

$$\vec{\mathbf{x}} = \langle \vec{x}_{\vec{\kappa}_1}, \vec{x}_{\vec{\kappa}_2}, \ldots, \vec{x}_{\vec{\kappa}_n} \rangle = \langle \vec{g}_1, \vec{g}_2, \ldots, \vec{g}_n \rangle \qquad (1)$$

Each of the n feature groups $\vec{g}_i$ is defined a priori by $\vec{\kappa}_i$, which indexes the dimensions in $\vec{\mathbf{x}}$ that belong to the i-th group. For example, we might group together individual words in an item's description into a single "description text" feature group. We define an *entity* to be a particular value or realization of a feature group. The number of dimensions of each group may vary, but all of the feature groups are embedded to the same space via their *feature extraction function* ϕ_i. These functions learn how to embed each feature group $\vec{g}_i$ and outputs a vector in $\mathbb{R}^r$. More, formally:

$$\hat{y}(\vec{\mathbf{x}}, \vec{\boldsymbol{\phi}}, \vec{\boldsymbol{\kappa}}) = \omega\left(\sum_{i=1}^{n} \sum_{j=i}^{n} \overbrace{\phi_i(\vec{x}_{\vec{\kappa}_i})}^{\substack{\text{group } i \\ \text{embedding}}} \cdot \overbrace{\phi_j(\vec{x}_{\vec{\kappa}_j})}^{\substack{\text{group } j \\ \text{embedding}}} \right) \qquad (2)$$

Here ω is an activation function. Intuitively, the dot product ($\cdot$) returns a scalar that measures the (dis)similarity between the embeddings of the feature groups. A simple implementation of ϕ_i is a linear fully-connected layer, where the output of the r-th entry is:

$$\phi_{i,r}\left(\vec{x}_i; \vec{\theta}_r\right)_r = \sum_{a=1}^{d_i} \theta_{r_a} x_{i_a} \qquad (3)$$

Other, more sophisticated functional forms of ϕ_i we have explored in our experiments include:

- A convolutional neural network that transforms a text sequence into a r-dimensional embedding. This function is able to preserve information in the order of a text sequence, unlike other methods for transforming text to numerical values such as bag-of-words.
- A deep, fully connected neural network that projects a scalar, such as average rating, into a r-dimensional embedding space. This extraction function, by treating the input as numerical, will require scalars close in value to have similar embeddings.

Any neural function that outputs a r-dimensional vector could be plugged into our framework as an extraction function ϕ.

Figure 1 compares existing factorization methods with our novel model in diagram form. Figure 1a shows a Factorization Machine (Rendle, 2010) that embeds each feature . In this example, Figure 1b shows Feat2Vec with two feature groups: the first group only has a single feature which is projected to an embedding (just like matrix factorization); but the second group has multiple features, which are together projected to a single embedding. Figure 1c shows an approach of using neural networks within factorization machines that has been proposed multiple times (Dziugaite and Roy, 2015; Guo et al., 2017). It replaces the dot product of factors with a learned neural function, which has been shown to improve predictive accuracy. The caveat of this architecture is that is no longer possible to interpret the embeddings as latent factors related to the target task.

In traditional factorization methods, individual item identifiers are embedded and thus need to be observed during training (i.e., cold-start problem). Feat2Vec can learn an embedding from an alternative characterization of the item—for example, an item's textual description. For this, we can treat the entire textual description as a feature group κ_i. A feature extraction function ϕ_i acts on the features in κ_i, and the other features interact with the words only via the output of ϕ_i.

The structure of the Feat2Vec model significantly expands previously published models. For example, Principal Component Analysis (PCA) is a common method to learn embeddings of individual dimensions of data. Although structured regularization techniques exist (Jenatton, Obozinski, and Bach, 2010), it is not obvious how to combine different dimensions in PCA when we are interested in treating a subset of dimensions as a single group, such as words in an item's description. Feat2Vec extends Factorization Machine (Rendle, 2010), in that we allow calculating embeddings for feature groups and we use feature extraction functions. StarSpace (Wu et al., 2017) introduces feature groups (called entities in their paper), but is only compatible with supervised tasks, constrains groups to be "bags of features", and is limited to two feature types. In contrast, Feat2Vec allows any number of groups to enter the model, and is compatible with diverse types of data, such as continuous features or ordered sequences.

Additionally, we introduce a new implicit sampling method that enables learning self-supervised embeddings for feature groups. Unlike Word2Vec, a popular self-supervised embedding algorithm, we do not constraint features types to be words. Instead, by grouping features using the hyperparameter $\vec{\boldsymbol{\kappa}}$ in Equation 2, the self-supervised model can reason on more abstract entities in the data. For example, in our experiments on a movie dataset, we are able to define a "genre" feature group, where we group non-mutually exclusive indicators for movie genres, including comedy, action, and drama films. This embedding may capture complex interactions between genre classifications typically unavailable through a tokenized treatment of genres.

2.2 Supervised Learning from Data

We can learn the the parameters of a Feat2Vec model $\boldsymbol{\theta}$ using training data by minimizing a loss function $\mathcal{L}$:

$$\arg\min_{\vec{\theta}} \sum_{x} \mathcal{L}\big(y(x), \hat{y}(x; \vec{\theta})\big) + \gamma ||\boldsymbol{\theta}||_2 \tag{4}$$

Here, $y(x)$ is the true target value for x obtained from training data, and $\hat{y}(x)$ is the one estimated by the model (Equation 2); $\boldsymbol{\theta}$ represents the parameters learned in during training (i.e. the parameters associated with the extraction functions ϕ_i). The hyperparameter γ controls the amount of regularization. For labeling and classification tasks, we optimize the binary cross-entropy.

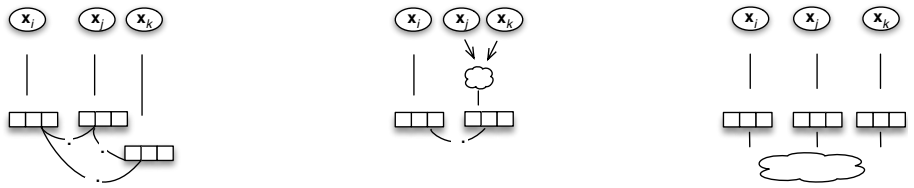
It is straightforward to optimize Equation 4 directly. Typically, this loss will be for a prediction task, and involve at least two feature groups—one of the feature groups is the target label that we want to predict, such as rating, and the other group(s) is the input from which we want to make the prediction, such as review text.

Consider a target feature group g_i that exists in a high dimensional space. This could be a one-hot encoding of a categorical variable with a large number of possible values. In such a scenario, it may be too costly to feed the model all negative labels, particularly if the model is sparse. In these cases, we can instead use a binary classifier with implicit sampling (Dyer, 2014), where we sample a fixed number (k) from the set of possible negative labels for each positively labeled record. This makes our Feat2Vec model feasible to implement for high-dimensional target features.

2.3 Self-supervised Learning From Data

We now discuss how Feat2Vec can be used to learn embeddings in an self-supervised setting with no explicit target for prediction.

The training dataset for a Feat2Vec model consists of the observed data. In natural language, these would be documents written by humans, along with document metadata. Since self-supervised Feat2Vec will require positive and negative examples during training, we supply unobserved data as negative examples. This is analogous to Word2Vec, which samples a negative instance from a noise distribution $\mathcal{Q}_{w2v}$ that is proportional to the empirical frequency of a word in the training data.



(a) **Factorization Machine** (b) **Feat2Vec** (c) **"Neural"**

Figure 1: **Network architectures for factorization models**. The white clouds (☁) represent deep layers, for example a convolutional network for text features, while the dots $(\cdot)$ denote dot products.

We start with a dataset S^+ of records with n feature groups. We then mark all observed records in the training set as our positive-labeled examples. For each positive record, we generate k negative labels using the 2-step algorithm documented in Algorithm 1:

Algorithm 1 Implicit sampling algorithm for self-supervised Feat2Vec

function FEAT2VEC_SAMPLE($S^+, k, \alpha_1, \alpha_2$)
  $S^- \leftarrow \emptyset$
  for $\vec{x}^+ \in S^+$ **do**
    Draw a random feature group $\kappa_i \sim \mathcal{Q}_1(\{\text{params}(\phi_i)\}_{i=1}^{|\vec{\kappa}|}, \alpha_1)$
    for $j \in \{1, \ldots, k\}$ **do**
      $\vec{x}^- \leftarrow \vec{x}^+$ ▷ set initially to be equal to the positive sample
      Draw a random entity $\tilde{x} \sim \mathcal{Q}_2(\mathrm{X}_{\kappa_i}, \alpha_2)$
      $\vec{x}^-_{\kappa_i} \leftarrow \tilde{x}$ ▷ substitute the i-th feature group with the sampled one
      $S^- \leftarrow S^- + \{\vec{x}^-\}$
    end for
  end for
  return S^-
end function

Explained in words, our negative sampling method for self-supervised learning iterates over all of the observations of the training dataset. For each observation $\vec{x}^+$, it randomly selects the i-th feature group from a noise distribution $\mathcal{Q}_1(\cdot)$. Then, it creates a negative observation that is identical to $\vec{x}^+$, except that its i-th entity is replaced by a value sampled from a noise distribution $\mathcal{Q}_2(\cdot)$. In our application, we use the same class of noise distributions (flattened multinomial) for both levels of sampling, but this need not be the case. We now describe the noise distributions that we use. Let $P_{\mathcal{Q}}(x)$ denote the probability of x under distribution $\mathcal{Q}$.

Sampling Feature Groups. To sample a feature group, we choose a feature group κ_i from a multinomial distribution with probabilities proportional a feature's complexity. By complexity, we mean the number of parameters we learn that are associated with a feature group's extraction function ϕ_i. This noise distribution places more weight on features that have more parameters and thus are going to require more training iterations to properly learn. The sampling probabilities of each feature group are:

$$P_{\mathcal{Q}_1}(\kappa_i | \text{ params}(\phi_i)\}_{i=1}^{|\vec{\kappa}|}, \alpha_1) = \frac{\text{params}(\phi_i)^{\alpha_1}}{\sum_{j=1}^{|\vec{\kappa}|} \text{params}(\phi_j)^{\alpha_1}} \tag{5}$$

where the function params calculates the complexity of a feature extraction function ϕ_i. For categorical variables using a linear fully-connected layer, the complexity is simply proportional to the number of categories in the feature group. However, if we have multiple intermediate layers for some feature extraction functions (e.g., convolutional layers), these parameters should also be counted towards a feature group's complexity. The hyper-parameter $\alpha_1 \in [0, 1]$ flattens the distribution. When $\alpha_1 = 0$, the feature groups are sampled uniformly, and when $\alpha_1 = 1$, they are sampled exactly proportional to their complexity.

Sampling Entities. To sample an entity within a feature group κ_i, we use a similar strategy to Word2Vec and sample from the empirical distribution of values:

$$P_{\mathcal{Q}_2}(x | \mathrm{X}_{\kappa_i}, \alpha_2) = \frac{\text{count}(x)^{\alpha_2}}{\sum_{x'_{\kappa_i} \in S^+} \text{count}(x'_{\kappa_i})^{\alpha_2}}, \quad \alpha_2 \in [0, 1] \tag{6}$$

Here, count(x) is the number of times a value x of feature group i appeared in the training dataset S^+ , and α_2 is again a flattening hyperparameter.

This method will sometimes by chance generate negatively labeled samples that *do* exist in our sample of observed records. The literature offers two solutions: in the Negative Sampling of Word2Vec, duplicate negative samples are ignored (Dyer, 2014). Instead, we account for the probability of random negative labels being identical to positively labeled data using *Noise Contrastive Estimation* (NCE) (Gutmann and Hyvärinen, 2010).

The Loss Function for Self-Supervised Learning For our self-supervised learning of embeddings, we optimize a NCE loss function, to adjust the structural statistical model $\hat{y} = p(y = 1 | \vec{x}, \vec{\phi}, \boldsymbol{\theta})$ expressed in Equation 2, to account for the possibility of random negative labels that appear identical to positively labeled data. Since in self-supervised learning we only deal with a dichotomous label, indicating a positive or negative sample, we restrict our attention to usage of Equation 2 with ω as a logistic link function.

An additional burden of NCE is that we need to calculate a partition function $Z_{\vec{x}}$ for each unique record type $\vec{x}$ in the data that transforms the probability $\hat{y}$ of a positive or negative label into a well-behaved distribution that integrates to 1. This would introduce an astronomical amount of computation and greatly increase the complexity of our model. Instead, we appeal to the work of Mnih and Teh (2012), who show that in the context of language models setting the $Z_{\vec{x}} = 1$ in advance does not change the performance of the model. The intuition is that if the underlying model has enough free parameters, it will effectively learn the probabilities itself, since systemic under/over prediction of probabilities will result in penalties on the loss function. Written explicitly, the new structural probability model is:

$$\tilde{p}(y = 1|\vec{x}, \vec{\phi}, \boldsymbol{\theta}) = \frac{\exp\big(s(\vec{x}|\vec{\phi}, \boldsymbol{\theta})\big)}{\exp(s(\vec{x}|\vec{\phi}, \boldsymbol{\theta}),) + P_{\mathcal{Q}}(\vec{x}|\alpha_1, \alpha_2)} \tag{7}$$

$$s(\vec{x}|\vec{\phi}, \boldsymbol{\theta}) = \sum_{i=1}^{|\vec{\kappa}|} \sum_{j=i}^{|\vec{\kappa}|} \phi_i(\vec{x}_{\vec{\kappa}_i}) \cdot \phi_j(\vec{x}_{\vec{\kappa}_j}) \tag{8}$$

$s(.)$ denotes the score of a record $\vec{x}$ given parameters/extraction functions, and $P_{\mathcal{Q}}(.)$ denotes the probability of a record $\vec{x}$ being drawn from our negative sampling algorithm, conditional on the positively labeled record $\vec{x}^+$ the negative sample is drawn for:

$$P_{\mathcal{Q}}(\vec{x}|\alpha_1, \alpha_2, \mathrm{X}, \vec{x}^+) = P_{\mathcal{Q}_2}(\vec{x}_{\boldsymbol{\kappa}_i}|\mathrm{X}_{\boldsymbol{\kappa}_i}, \boldsymbol{\kappa}_i, \alpha_2) \times P_{\mathcal{Q}_1}(\boldsymbol{\kappa}_i|\,\mathrm{params}(\phi_i)\}_{i=1}^{n}, \alpha_1)$$

Our loss function L optimizes $\boldsymbol{\theta}$, the parameters of the feature extraction functions $\vec{\phi}$, while accounting for the probability of negative samples.

$$L(S) = \arg\min_{\boldsymbol{\theta}} \frac{1}{|S^+|} \sum_{\vec{x}^+ \in S^+} \Big(\log(\tilde{p}(y = 1|\vec{x}^+, \vec{\phi}, \boldsymbol{\theta})) + \sum_{\vec{x}^- \sim \mathcal{Q}(\cdot|\vec{x}^+)}^{k} \log(\tilde{p}(y = 0|\vec{x}^-, \vec{\phi}, \boldsymbol{\theta}))\Big)$$

Feat2Vec has interesting theoretical properties. With n feature groups, the loss function of self-supervised Feat2Vec can be shown to be equivalent to a convex combination of the losses from n supervised Feat2Vec models with implicit sampling (proof omitted). In other words, it optimizes n multi-label classifiers, where each classifier is optimized for a different target feature group. Intuitively, during sampling in self-supervised Feat2Vec, we choose a random target feature group according to $P_{\mathcal{Q}_1}$, and then add that specific group's supervised loss to the total self-supervised loss.

3 Empirical Results

3.1 Supervised Embeddings

We now address our working hypotheses for evaluating supervised embeddings. We evaluate on the Yelp dataset[1], which consists of 4.7 million reviews of restaurants. For all of our experiments, we define a development set and a single test set which is 10% of the dataset, and a part of the development set is used for early stopping or validating hyper-parameters. We use mean squared error (MSE) as the evaluation metric for predicting ratings in the Yelp dataset. We share most of the code for the experiments online[2].

Table 1: Supervised Yelp rating prediction

	MSE	Improvement over MF
Feat2Vec	**0.480**	**69.2** %
DeepCoNN	1.441	19.6 %
MF (Matrix Factorization)	1.561	-

We build 3 feature groups for this task: item (restaurant) identifiers, user identifiers, and review text. We use a standard linear (Equation 3) extraction functions ϕ on each one-hot encoding representation of users and items. For our feature extraction function for review text, we use a Convolutional Neural Network (CNN), which has been shown to be effective for natural language tasks (Kalchbrenner, Grefenstette, and Blunsom, 2014; Weston, Chopra, and Adams, 2014). Instead of tuning the hyper-parameters, we follow previously published guidelines (Zhang and Wallace, 2015).

Comparison with alternative CNN-based text factorization We now compare with a method called DeepCoNN, a deep network specifically designed for incorporating text into matrix factorization (Zheng, Noroozi, and Yu, 2017), a state of the art method for predicting customer ratings when text reviews are available. To make results comparable, the Feat2Vec experiments use the same feature extraction function used by DeepCoNN. For each user-item pair, DeepCoNN concatenates the text from all reviews for that item and all reviews by that user. The concatenated text is then fed into a feature extraction function for each entity, followed by a factorization machine.

Table 1 compares our methods to DeepCoNN's published results because a public implementation is not available. Feat2Vec provides a large performance increase when comparing the reported improvement in the mean squared error (MSE) over Matrix Factorization, Our approach is more general, and we claim that it is also more efficient. Since DeepCoNN concatenates text, when the average reviews per user is $\bar{n_u}$ and reviews per item is $\bar{n_i}$, each text is duplicated on average $\bar{n_i} \times \bar{n_u}$ times per training epoch. In contrast, for Feat2Vec each review is seen only once per epoch. Thus it can be 1-2 orders of magnitude more efficient for datasets where $\bar{n_i} \times \bar{n_u}$ is large.

[1] https://www.yelp.com/dataset/challenge

[2] `https://goo.gl/zEQBiA`

3.2 Self-Supervised Embeddings

The prediction of similar or related words is a commonly used method for evaluating self-supervised word embeddings (Bojanowski et al., 2016; Mikolov et al., 2013a). Since our algorithm is designed for multi-modal data, we generalize this task for multiple feature types as follows. Given a dataset with n feature groups $g_1, g_2, \ldots g_n$ we have trained a self-supervised Feat2Vec model on, we choose one group g_i as the "target" and a group g_j as the predictor. Given a held-out instance, we rank all possible values of the target group by cosine similarity to the predictor group's embedding $\phi_j(\vec{x}_{\mathcal{K}_j})$ for that instance. We then retrieve the ranking of the actual target entity for the held-out instance in the test dataset. Rankings are evaluated according to their mean percentile rank (MPR): $MPR = \frac{1}{N}\sum_{i=1}^{N} R_i/(\max R)$, where R_i is the the target entity rank for instance i. A score of 0 would indicate perfect performance (i.e. top rank every test sample given), so a lower value is better under this metric. We will use this method to compare the performance of Feat2Vec algorithm and compare its performance to Word2Vec's CBOW algorithm for learning embeddings. In our experiments, we set $\alpha_1 = .25$, $\alpha_2 = 0.75$, $k = 5$ and $r = 50$. We evaluate self-supervised Feat2Vec on 3 datasets:

Movies The Internet Movie Database (IMDB) is a publicly available dataset[3] of information related to films, television programs and video games. We limit our experiments to data on its 465,136 movies. Table 2 summarizes our feature groups. For categorical features within a group, we learn a unique embedding for each value. For groups with multiple categories, we use a "Bag of categories" approach to produce a group embedding. For example, we sum learned embeddings of individual actors such as Tom Cruise to produce a single "actor" feature group embedding associated with a title. For real-valued features, we pass the scalar output through a fully-connected 3-layer neural network to output an r-dimensional embedding.

Education We use a dataset from an anonymized leading technology company that provides educational services. In this proprietary dataset, we have 57 million observations and 9 categorical feature types which include textbook identifier, user identifier, school identifier, along with other proprietary features. Each observation is an interaction a user had with a textbook.

Yelp We use the Yelp dataset from our supervised experiments to evaluate the efficacy of self-supervised embeddings in ratings prediction.

Results After training IMDB embeddings, we use cast members associated with movies in the test set and predict the actual director of the film. For the educational dataset, we directly retrieve the most similar textbooks to the user embedding.

Table 2: IMDB Feature Groups

Feature Group	Type	# of feats.
Runtime (minutes)	Real-valued	1
IMDB rating (0-10)	Real-valued	1
# of rating votes	Real-valued	1
Is adult film?	Categorical	2
Movie release year	Categorical	271
Movie title	Bag of Words	165,471
Directors	Bag of categories	174,382
Genres	Bag of categories	28
Writers	Bag of categories	244,241
Principal actors	Bag of categories	1,104,280

Table 3 presents our evaluation results. Feat2Vec outperforms CBOW in the MPR metric. Additionally, while CBOW predicts the actual director 1.26% of the times, Feat2Vec does so 2.43% of the time, a 92% improvement in Top-1 Precision over CBOW.

Table 3: Mean percentile rank

Dataset	Feat2Vec	CBOW
IMDB	19.36%	24.15%
Educational	25.2%	29.2%

3.3 Self-Supervised Feat2Vec Performance with Continuous Inputs

We now focus on how well Feat2Vec performs on a real-valued feature. We expect this task to highlight Feat2Vec's advantage over token-based embedding learning algorithms, such as Word2Vec. Our rating embedding extraction function (a 3-layer NN) will require embeddings of numerically similar ratings to be close, while Word2Vec will treat two numerically different ratings as completely different entities. We evaluate the prediction of test dataset ratings by choosing the rating embedding most similar[4] to the embedding of the movie's director, and compute the MSE of the predicted rating in the test dataset. Feat2Vec scores an MSE of 6.6, while Word2Vec (CBOW) scores 9.3.

We also use the Yelp dataset, predicting the most similar rating embedding to the review text embeddings produced by Feat2Vec, Word2Vec (CBOW), and Doc2Vec (DM). Doc2Vec is only used for the Yelp dataset because there is no clear "document" in the IMDB dataset, while in the Yelp dataset the review text is a natural candidate. For Word2Vec and Doc2Vec, the review text embedding is the average of word embeddings, analogous to the context vector used for learning in these algorithms. Figure 2 reports the confusion matrices for each model from this experiment. In general, Word2Vec is poor in its predictive power, predicting 5 stars for

[3] http://www.imdb.com/interfaces/

[4] As before, the metric is cosine similarity.

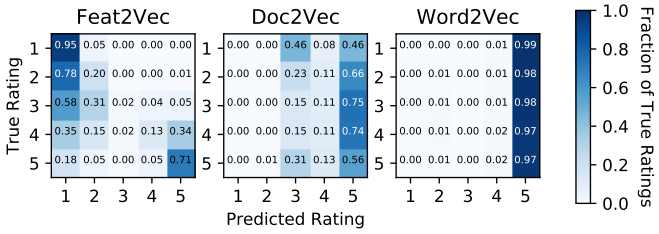


Figure 2: Confusion Matrices of Self-Supervised Yelp Ratings Predictions

97% of the test sample. Though Feat2Vec and Doc2Vec yield comparable MSE (2.94 vs. 2.92, respectively), Feat2Vec outperforms Doc2Vec by a substantial margin in classification error rate (55% vs. 73%) and mean absolute error (1.13 vs. 1.31). As made evident by the figure, Doc2Vec is unable to identify low rating reviews: only 0.4% of Doc2vec predictions are ≤ 2 stars, despite this comprising 20% of the data. In contrast, Feat2Vec is more diverse in its predictions, and better able to identify extreme reviews.

4 Conclusion

Embeddings have proven useful in a wide variety of contexts, but they are typically built from datasets with a single feature type as in the case of Word2Vec, or tuned for a single prediction task as in the case of Factorization Machine. We believe Feat2Vec is an important step towards general-purpose methods, because it decouples feature extraction from prediction for datasets with multiple feature types, it can be self-supervised, and its embeddings are easily interpretable.

In the supervised setting, Feat2Vec is able to calculate embeddings for passages of texts. We show results outperforming an algorithm specifically designed for text—even when using the same feature extraction CNN.

In the self-supervised setting, Feat2Vec exploits the structure of a dataset to learn embeddings in a more sensible way than existing methods. This yields performance improvements in our ranking and prediction tasks. To the extent of our knowledge, Self-Supervised Feat2Vec is the first method to calculate continuous representations of data with multi-modal feature types and no explicit labels.

Future work could study how to reduce the amount of human knowledge our approach requires; for example by automatically grouping features into entities, or by automatically choosing a feature extraction function. These ideas can extend to our codebase that we make available [5]. Though further experimentation is necessary, we believe that our results are an encouraging step towards general-purpose embedding models.

[5]The code for the Feat2Vec algorithm is available here and the experiments using the IMDB data can be found here.

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