Semantic similarity in Q&A using Deep learning techniques

Master's Thesis Project report submitted

in partial fulfilment for the award of the degree of

Masters of Technology

in

Computer Science and Engineering

by

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Spring Semester, 2016-17

April 28, 2017

DECLARATION

I certify that

(a) The work contained in this report has been done by me under the guidance of my supervisor.

(b) The work has not been submitted to any other Institute for any degree or diploma.

(c) I have conformed to the norms and guidelines given in the Ethical Code of Conduct of the Institute.

(d) Whenever I have used materials (data, theoretical analysis, figures, and text) from other sources, I have given due credit to them by citing them in the text of the thesis and giving their details in the references. Further, I have taken permission from the copyright owners of the sources, whenever necessary.

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CERTIFICATE

This is to certify that the project report entitled "**Semantic similarity in Q&A using Deep learning techniques**" submitted by **Sandesh C** (Roll No. 12CS30041) to IIT Kharagpur towards partial fulfilment of requirements for the award of degree of Masters of Technology in Computer Science and Engineering is a record of bona fide work carried out by him under my supervision and guidance during Spring Semester, 2016-17.

Date: April XX, 2017
Place: Kharagpur

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Abstract

Community Question Answering (CQA) forums have since long been plagued with the problem of answer reranking, to automate the process of finding good comments to a question. Here in this work, we take up the problem of Question-Comment similarity with a simple approach where a question-comment pair is represented as concatenation of: distributed paragraph vector representations of question text, comment text and centroidal comment (of that question), along with various syntactic and metadata features. A multilayer perceptron is used to compute the similarity scores for such a question-commnet pair.

Despite it's simplicity the model attains competitive results compared to the best submissions at SemEval '16 Task 3 - Community Question Answering (Subtask A).

Acknowledgements

First and foremost I would like to thank my guide, Prof. Pawan Goyal, for providing an opportunity to work on a challenging and relevant problem, that has blossomed to be a great learning experience. I also thank Prof. Pawan Goyal, for the constant support and guidance over the course of the project.

I would like to thank our faculty advisor, Prof. Rajat Subhra Chakraborty, for his continued efforts to help and enrich the academic experience our batch on vairous occasions. Also to acknowledge, the Department of Computer Science and Engineering, IIT Kharagpur, has been helpful through providing easy access to substantial resources for computation.

Finally I would like to thank my parents, family and friends for their continued belief and support through out the course of the programme.

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Abbreviations

CQA	**C**ommunity **Q**uestion **A**nswering
QL	**Q**atar **L**iving
SGD	**S**tochastic **G**radient **D**escent
PV	**P**aragraph **V**ector
CBOW	**C**ontinious **B**ag-**O**f-**W**ords
DM	**D**istributed **M**emory
DBOW	**D**istributed **B**ag-**O**f-**W**ords
MAP	**M**ean **A**veraged **P**recision
MRR	**M**ean **R**eciprocal **R**ate
AvgRec	**Av**era**g**e **Rec**all
P	**P**recision
R	**R**ecall
Acc	**Acc**uraccy

Introduction

1.1 Introduction

CQA forums such as Stack Overflow[1] and Qatar Living[2], are gaining popularity online. These forums are seldom moderated, quite open, and thus they typically have little restrictions, if any, on who can post and who can answer a question. On the positive side, this means that one can freely ask any question and can then expect some good, honest comments. On the negative side, it takes effort to go through all possible comments and to make sense of them. For example, it is not unusual for a question to have hundreds of comments, which makes it very time-consuming for the user to inspect and to winnow through them all. The present work is intended to automate the process of finding good comments to questions in a community-created discussion forum, by automatically ranking the existing comments.

1.2 SemEval Task – 3

SemEval Tasks[3] (Semantic Evaluation) are an ongoing series of evaluations of computational semantic analysis systems. The **SemEval Task 3** in particular deals with semantic comparison for words and texts in the domain of Community Question

[1] https://stackoverflow.com/
[2] http://www.qatarliving.com/
[3] http://alt.qcri.org/semeval2017/

Answering (CQA). In essence, the main CQA task can be defined as follows: *"given (i) a new question and (ii) a large collection of question-comment threads created by a user community, rank the comments that are most useful for answering the new question"*.

1.2.1 Subtask A – Question-Comment Similarity

In this project we address the CQA task by exploiting the semantic similarity in Q&A using Deep learning techniques. In particular we focus on a single subtask under **SemEval - Task 3**, namely the **Subtask A**.

Subtask A *Given a question from a question-comment thread, rank the comments as per their relevance (similarity) with respect to the question.*

1.3 Thesis Organization

The thesis is further organized as follows: Chapter 2 addresses the recent works pertaining to the task of finding question-comment similarity, and also sheds light on a few such works that use Deep Learning methodologies to solve this problem; Chapter 3 then provides a detailed explanation of the multilayer perceptron based prediction model approach adopted in our work, using distributed document representations and various syntactic, metadata features. Finally, Chapter 4 tabulates the results obtained with our approach on SemEval '16 Task 3 - Subtask A dataset, which we shall see are competitive with the best results published at the same event.

Literature Survey

The tasks falling under the Community Question & Answering section of SemEval goes in the direction of passage reranking, where automatic classifiers are normally applied to pairs of questions and comment passages to derive a relative order between passages. This is in other words the task of Answer re-ranking.

In recent years, many advanced models have been developed for automating answer selection, producing a large body of work. For instance, Wang et al. (2007) proposed a probabilistic quasi synchronous grammar to learn syntactic transformations from the question to the candidate answers; Heilman and Smith (2010) used an algorithm based on Tree Edit Distance (TED) to learn tree transformations in pairs; Wang and Manning (2010) developed a probabilistic model to learn tree-edit operations on dependency parse trees; and Yao et al. (2013) applied linear chain CRFs with features derived from TED to automatically learn associations between questions and candidate answers. One interesting aspect of the above research is the need for syntactic structures; this is also corroborated in [Severyn and Moschitti (2012); Severyn and Moschitti (2013)]. Note that answer selection can use models for textual entailment, semantic similarity, and for natural language inference in general.

Although recently quite a few work in this domain have started to adopt Deep Learning Techniques to solve the problem of answer re-ranking. For eg. Lin and Wang (2015) treated the answer selection task as a sequence labeling problem and proposed recurrent convolutional neural networks to recognize good comments. In a follow-up work, Zhou et al. (2015) included long-short term memory (LSTM) units in their convolutional neural network to learn the classification sequence for the thread. In parallel, Barrón-Cedeno et al. (2015) exploited the dependencies between the thread comments to tackle the same task. This was done by designing features that look globally at the thread and by applying structured prediction models, such as Conditional Random Fields Lafferty et al. (2001).

This research direction was further extended by Joty et al. (2015), who used the output structure at the thread level in order to make more consistent global decisions. For this purpose, they modeled the relations between pairs of comments at any distance in the thread, and they combined the predictions of local classifiers in a graph-cut and in an ILP frameworks.

Noteably, at SemEval-2015 Task 3, Shafiq Joty and Nakov (2016) proposed two novel joint learning models that are on-line and integrate inference within the learning process. The first one jointly learns two node- and edge-level MaxEnt classifiers with stochastic gradient descent and integrates the inference step with loopy belief propagation. The second model is an instance of fully connected pairwise CRFs (FCCRF). The FCCRF model significantly outperformed all other approaches and yielded the best results on the task (SemEval-2015 Task 3). Crucial elements for its success were the global normalization and an Ising-like edge potential.

Thus influenced by the trend we shall tread in the direction of exploring Deep Learning Techniques to effectively solve the problem of finding Question - Comment similarity; building on the success of previous attempts. Note that we use the terms relevant-comment and answer interchangeably thoughout the document.

Approach

For this task, we adopt a neural approach to open-domain non-factoid QA developed by Bogdanova and Foster (2016), which focused on "answer re-ranking", i.e. given a list of candidate answers to a question, order the answers according to their relevance to the question. The approach is very simple and requires no feature engineering. Question-answer pairs are represented by concatenated distributed representation vectors and a multilayer perceptron is used to compute the score for an answer (the probability of an answer being the best answer to the question). Despite its simplicity, their work achieved state-of-the-art performance on the Yahoo! Answers dataset of manner or How questions introduced by Jansen et al. (2014). This improved performance was attributed to the use of paragraph vector representations instead of averaging over word vectors, and to the use of suitable data for training these representations. This project aims at improving the simplistic model proposed by Bogdanova and Foster (2016) with a few enhancements to achieve state-of-art performance at the **SemEval Task 3 - Subtask A** of finding Question – Comment similarity.

It is for this reason we use Paragraph Vectors (Le and Mikolov (2014)) for quantifying the question-comment text documents. Paragraph Vector is an unsupervised framework that learns continuous distributed vector representations for pieces of texts. The texts can be of variable-length, ranging from sentences to documents.

The name Paragraph Vector is to emphasize the fact that the method can be applied to variable-length pieces of texts, anything from a phrase or sentence to a large document.

3.1 Learning Algorithm

We used a simple feedforward neural network, i.e. a multilayered perceptron, to predict the best answer as performed by Bogdanova and Foster (2016). As shown in Figure 3.1, the first layer of network takes the vector representation for a question-comment pair *(q, c)* as input, which is a concatenation of the distributed representations q and c for the question and the comment respectively. Each representation is a real-valued vector of a fixed dimensionality d, which is a parameter to be tuned. The input layer is concatenated with another d dimensional vector, namely the centroidal comment, which is centroid of the distributed representation of all comments to the question q (subsection 3.3.1). This is further concatenated with another set of features generated from the pair (q, c) as described in section 3.3. The latter two enhancements is the reason our approach shall improve upon the performance achieved by Bogdanova and Foster (2016).

This layer is then followed by one or more hidden layers, the number of layers and units in each of these layers are also parameters to be experimentally tuned. We consider the activation function as well to be a parameter to be tuned by exprimentation. Finally, a softmax layer is used to compute the output probability p, i.e. the probabilities p1 and p2 of the negative (i.e. not best answer) and positive (i.e. best answer) classes respectively. For each question, all its user-generated comments are ranked according to their probability of being the best answer, as predicted by the network.

Given a question-comment pair (q, c), the possible values for the ground-truth label are 1 (best answer) and 0 (not a best answer). The network is trained by minimizing

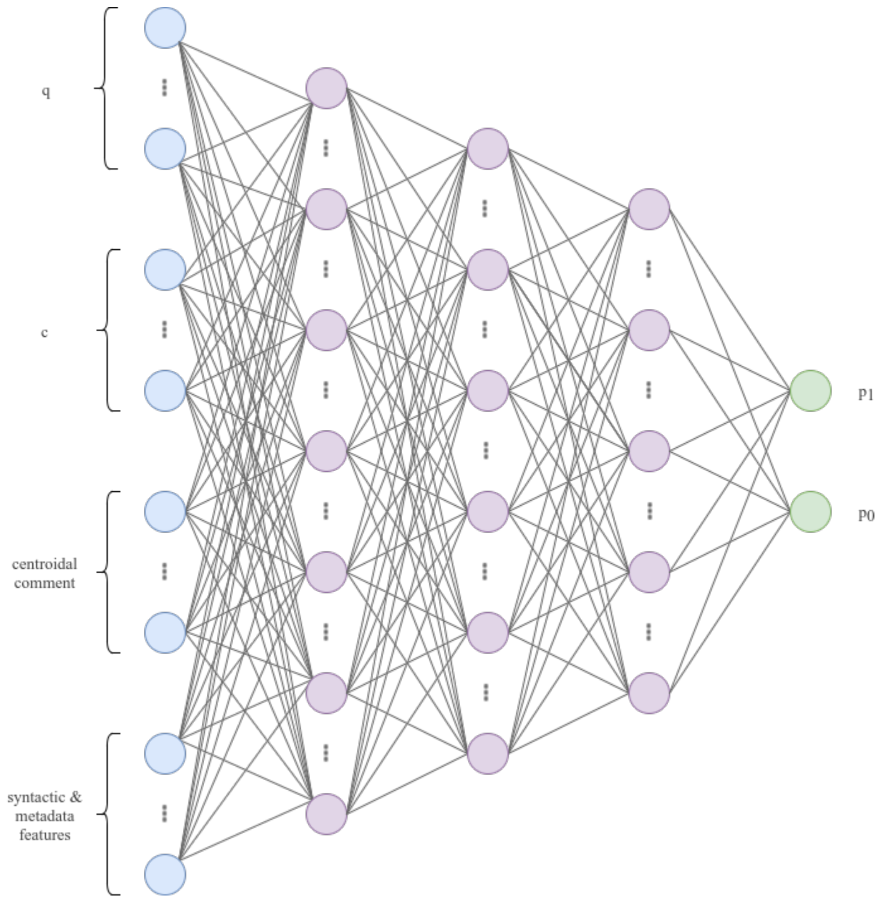

FIGURE 3.1: Architecture of proposed Feedforward Neural Network

the L2-regularized cross-entropy loss function between the ground-truth labels and the network predictions on the training set. We use either stochastic gradient descent (SGD) or Adam solver and early stopping to minimize the loss over the training set.

3.2 Document Representations

This approach requires question-comment pairs to be represented as a fixed-size vector. We experimentally evaluate the Paragraph Vector model (PV) proposed by Le and Mikolov (2014). The PV is an extension of the widely used continuous bag-of-words (CBOW) and skip-gram word embedding models, known as word2vec.

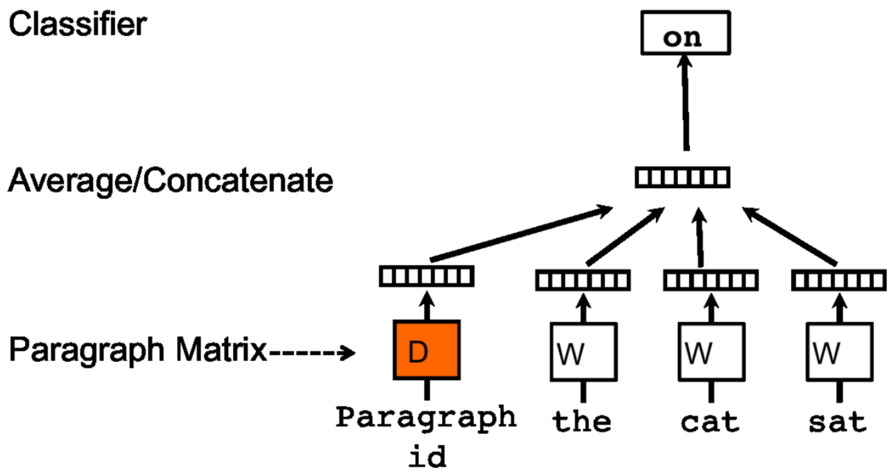

Figure 3.2: Distributed Memory (DM) framework for learning paragraph vector. In this model, the concatenation or average of word vectors with a context of few words is used to predict the next word. The paragraph vector represents the missing information from the current context and can act as a memory of the topic of the paragraph.

However, in contrast to CBOW and skip-gram models that only learn word embeddings, the PV is able to learn representations for pieces of text of arbitrary length, e.g. sentences, paragraphs or documents. The types of PV include (1) the distributed memory (DM) model, that predicts the next word in a text window using the concatenation of the word vectors of previous words and the paragraph vector; (2) the distributed bag-of-words (DBOW) model, that – similar to the skip-gram model – predicts words (in a small window) randomly sampled from the paragraph, given the paragraph vector. We experiment with both DM and DBOW models. Figure 3.2 and Figure 3.3 provide an illustration for these paragraph vector models. Also, note that we shall use the terms paragraph vector (PV) and document vector/representation interchangeably.

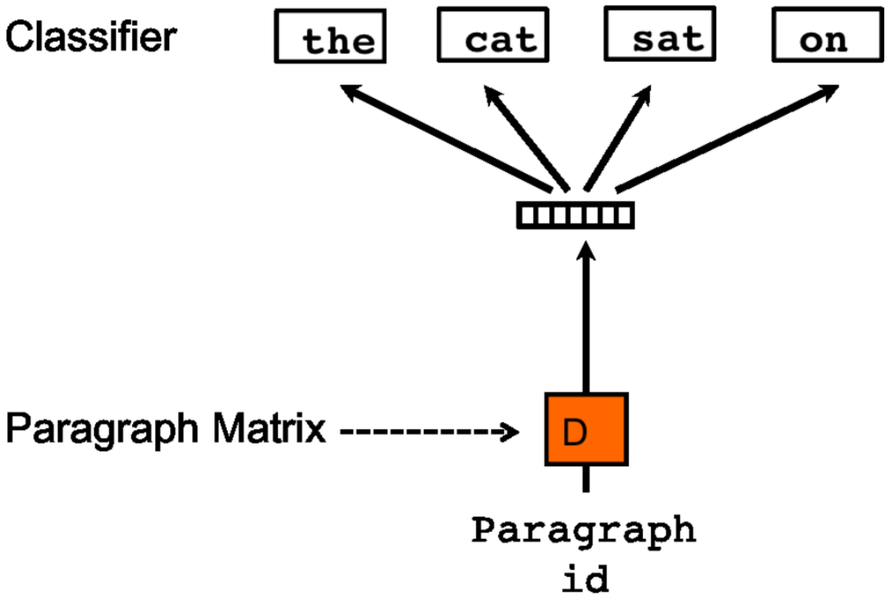

FIGURE 3.3: Distributed Bag of Words (DBOW) version of paragraph vectors. The paragraph vector is trained to predict the words in a small window

3.3 Feature Set

Apart from paragraph vectors of the Question (q) and Comment (c) that the feed-forward network takes as input, we describe below the surplus features incorporated in our model:

3.3.1 Centroidal Comment

Inorder to rank the comments, it is only intuition that we must use the information in other comment texts to accurately provide relative relevance scores, which in turn reflects the rank, for comment texts. It is for this reason we introduced the centroidal comment, denoted as avg_com_q, computed as:

$$avg\_com_q = \frac{\sum\limits_{c \in q} c}{||\sum\limits_{c \in q} c||} \tag{1}$$

3.3.2 Syntactic and Metadata Features

We used several semantic vector similarity and metadata feature groups as mentioned in Mihaylov and Nakov (2016). For the ease of the reader, we shall describe the same feature groups below.

Note that for the similarity measures mentioned below, we used cosine similarity:

$$1 - \frac{u.v}{||u||.||v||} \tag{2}$$

Semantic Word Embeddings. We used semantic word embeddings obtained from Word2Vec models trained on the unannotated data set from QatarLiving. For each piece of text such as comment text, question body and question subject, we constructed the centroid vector from the vectors of all words in that text (excluding stopwords).

$$centroid(w_{1...n}) = \frac{\sum_{i=1}^{n} w_i}{n} \tag{3}$$

We construct centroid vectors (3) from the question text (subject + body) and the comment text to design various features as described below.

Semantic Vector Similarities. We used various similarity features calculated using the centroid word vectors on the question text (subject + body) and on the comment text, as well as on parts thereof:

Question to Answer similarity. We assume that a relevant answer should have a centroid vector that is close to that for the question. We used the question text to comment text vector similarities.

Maximized similarity. We ranked each word in the comment text to the question text centroid vector according to their similarity and we took the average similarity of the top N words. We took the top 1, 2, 3, 4 and 5 words similarities as features.

The assumption here is that if the average similarity for the top N most similar words is high, then the comment might be relevant.

Aligned similarity. For each word in the question text, we chose the most similar word from the comment text and we took the average of all best word pair similarities as suggested in Tran et al. (2015).

Part of speech (POS) based word vector similarities. We performed part of speech tagging using the Stanford tagger Toutanova et al. (2003), and we took similarities between centroid vectors of words with a specific tag from the comment text and the centroid vector of the words with a specific tag from the question text. The assumption is that some parts of speech between the question and the comment might be closer than other parts of speech.

Word clusters (WC) similarity. We clustered the word vectors from the Word2Vec vocabulary in 1,000 clusters using K-Means clustering. We then calculated the cluster similarity between the question body word clusters and the answer text word clusters. For all experiments, we used clusters obtained from the Word2Vec model trained on QatarLiving forums with vector size of 100, window size 10.

LDA topic similarity. We performed topic clustering using Latent Dirichlet Allocation (LDA) as implemented in the gensim toolkit Rehurek and Sojka (2010) on Train1 + Train2 + Dev questions and comments. We built topic models with 100 topics. For each word in the question text and for the comment text, we built a bag-of-topics with corresponding distribution, and calculated similarity. The assumption here is that if the question and the comment share similar topics, they are more likely to be relevant to each other

Paragraph Vector similarities. The similarity among the distributed vector representations of question text (q), answer text (a) and the centroidal answer (avg_com_q), taken two at a time are also included.

Metadata. In addition to the semantic features described above, we also used some common sense metadata features:

Answer contains a question mark. If the comment has an question mark, it may be another question, which might indicate a bad answer.

Answer length. Assumption here is that longer answers could bring useful details.

Question length. If the question is longer, it may be more clear, which may help users give a more relevant answer.

Question to comment length. If the question is long and the answer is short, it may be less relevant.

The answer's author is the same as the corresponding question's author. If the answer is posted by the same user who posted the question and it is relevant, why has he/she asked the question in the first place?

Answer rank in the thread. Earlier answers could be posted by users who visit the forum more often, and they may have read more similar questions and answers. Moreover, discussion in the forum tends to diverge from the question over time.

Question category. We took the category of the question as a sparse binary feature vector (a feature with a value of 1 appears if question is in the category). The assumption here is that the question-comment relevance might depend on the category of the question.

Comments by the same User. The number of comments by the author of a given comment to the same question and the order of the comments (first, second, ...) is also included as a feature. If the author produced an incomplete answer in the first attempt, he/she might be obliged to produce another comment subsequently.

Time difference between Question and Comment posting. Immediate comments could reflect incomplete answers to longer questions, while comments posted after substantial time might reflect well-thought answers.

Experiments

4.1 Data

Though Bogdanova and Foster (2016) experiments with the *Yahoo! Answers dataset*[4], we have used the data provided as a part of the popular **SemEval Task 3** for **Subtask A** (Nakov et al. (2016)). Table 1 contains the statistics about the forementioned dataset. This dataset contains about 42K (q, c) pairs to learn from; spreading over about 5.4K questions. We shall refer to this data as the CQA-QL corpus in future. Further we also use a large unannotated dataset, released by the same source, from Qatar Living with 189,941 questions and 1,894,456 comments, which is used for unsupervised learning/training domain-specific word/document embeddings.

Category	**Train (Part-I)**	**Train (Part-II)**	**Train+Dev+Test (from SemEval 2015)**	**Dev**	**Test**	**Total**
Questions	**1,411**	**379**	**2,480+291+319**	**244**	**327**	**5,451**
Comments	**14,110**	**3,790**	**14,893+1,529+1,876**	**2,440**	**3,270**	**41,908**
-Good	*5,287*	*1,364*	*7,418+813+946*	*818*	*1,329*	*17,975*
-Bad	*6,362*	*1,777*	*5,971+544+774*	*1,209*	*1,485*	*18,122*
-Potentially	*2,461*	*649*	*1,504+172+156*	*413*	*456*	*5,811*

Table 1: Statistics on English CQA-QL corpus from SemEval-2017 Task 3 (Subtask A)

[4] http://webscope.sandbox.yahoo.com/

4.2 Experimental Setup

We use the gensim[5] implementation of DM and DBOW paragraph vector models. The data for training the unsupervised *doc2vec* model (PV model) is the forementioned large unannotated dataset from Qatar Living forums. Each paragraph (q or c) was converted to lowercase, tokenized by space character and cleaned of stop words before training *doc2vec* models. The parameters of training these models being the window size (maximum distance between the predicted word and context words used for prediction within a document) and number of epochs of training, were cross-validated to give low errors on the training dataset. We further use normalized versions of the document vector representations thus generated, to be fed as inputs to the feedforward neural network described in section 3.1.

For the implementation of the feedforward neural network as described in section 3.1, we shall use the popular python library *scikit-learn*[6]'s *MLPClassifier*[7].

4.3 Results

4.3.1 Document Vector Representations

For training each question/comment text was treated as a document/paragraph and assigned a label, which can be used as a key to retrieve the document vector. Furthermore post training the doc2vec model is able to infer a document vector for any new question/comment text whose vocabulary is from the original corpus. The errors post training is computed as averaged squared error over all question/comment text, by computing squared error between the document vector learnt by the model corresponding to the text's label and the document vector inferred from the

[5]https://radimrehurek.com/gensim/models/doc2vec.html
[6]http://scikit-learn.org/stable/index.html
[7]http://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

question/comment text. The squared errors are computed for normalizeddocument vectors. For comparison purposes squared error between any two random (normalized) document vector is tabulated beside these errors (averaged over as many iterations as the number of question/comment text). Experiments show that 100-dimensional PV trained over the ∼2.3M samples from the unannotated QL corpus, gives sufficiently low errors post normalization. Further more, PV-DBOW proves to outperform the PV-DM representations as seen in Table 2. It contains few of the best results has rows sorted by the value of *column 'Ratio'*, as it is the indicator of how good the representation is. The complete list of experiments are tabulated under Table 7 in Appendix A.

Category	**Window Size**	**Epochs**	**Normalized Sq. Error (A)**	**Norm. Sq. Error (Random) (B)**	**Ratio (B/A)**
PV-DBOW	10	5	0.14	0.80	5.89
PV-DBOW	10	10	0.14	0.83	5.84
PV-DM	10	5	0.21	0.99	4.67
PV-DM	15	10	0.22	0.98	4.47

Table 2: Training document vector representations PV-DM and PV-DBOW – Best results

To decide upon the dimension of the paragraph vectors we conduct similar experiments by testing on PV-DBOW document vectors of size 100 and 200. The best results tabulated in Table 3, show that 100 dimensional paragraph vectors prove to be a better choice owing to having both: higher accuracy and low computational complexity. The complete list of experiments are tabulated under Table 8 in Appendix A.

Dimension	**Window Size**	**Epochs**	**Normalized Sq. Error (A)**	**Norm. Sq. Error (Random) (B)**	**Ratio (B/A)**
100	10	5	0.14	0.80	5.89
100	10	10	0.14	0.83	5.84
200	10	10	0.15	0.84	5.65
200	10	5	0.15	0.82	5.47

Table 3: Training PV-DBOW document vectors of sizes 100 and 200 – Best results

4.3.2 SemEval Task 3 – Subtask A

The training data comprises of 38,638 comments spanning over 5,124 questions. The neural net input is a tuple of the form $(q, c, avg\_ans_q, ft_{(q,c)})$, where,

avg_com_q is (normalized) average over the PV of all comments to question q

$ft_{(q,c)}$ is feature vector corresp. to the pair (q,c) as described in section 3.3

SemEval Task 3 has as an official evaluation measure used to rank the participating systems, the metric of Mean Average Precision (*MAP*), calculated for the ten comments a participating system has ranked highest. Further metrics such as Mean Reciprocal Rank (*MRR*) and Average Recall (*AvgRec*) for top-10 results; Precision (*P*), Recall (*R*), *F1* (with respect to the Good/Relevant class) and Accuracy (*Acc*) are also reported.

4.3.2.1 Preliminary experiments with (q, c) inputs

Intially experiments were conducted with only (q, c) pair as input to the neural nets. The nets were trained using multiple solvers, activation functions, hidden layer configurations. The best performance for each parameter configuration is as tabulated in Table 4, while the complete results are tabulated in Appendix B.

Category	**Solver**	**Activation**	**MAP**	**AvgRec**	**MRR**	**P**	**R**	**F$_1$**	**Acc**
PV-DBOW	Adam	logistic	**0.7049**	0.8292	77.62	0.6601	0.5508	0.6005	0.7021
PV-DBOW	SGD	relu	0.7019	0.8251	77.16	0.6327	0.5937	0.6126	0.6948
PV-DBOW	SGD	logistic	0.7018	0.8242	77.32	0.6412	0.5877	0.6133	0.6988
PV-DBOW	SGD	tanh	0.7009	0.8245	76.62	0.6339	0.5914	0.6119	0.6951
PV-DBOW	Adam	relu	0.6993	0.8106	76.94	0.5998	0.5741	0.5867	0.6713
PV-DBOW	Adam	tanh	0.698	0.8231	76.35	0.6386	0.5546	0.5936	0.6914
PV-DM	SGD	relu	0.6578	0.7855	74.58	0.5793	0.5357	0.5567	0.6532

TABLE 4: Preliminary experiments using only (q, c) inputs – Best results

PV-DBOW clearly outperforms PV-DM representations in these preliminary runs. Building on this, further experiments where conducted using only the PV-DBOW representations.

4.3.2.2 Improvement with inclusion of Centroidal comment

As described in subsection 3.3.1, additionally, to capture the relative goodness of an comment with respect to other comments to the same question, avg_com_q (normalized post averaging over the PV of all comments to question q) was fed as an input to the neural net. The best results for these experiments are tabulated in Table 5. Complete results are tabulated under Appendix C.

Category	Solver	Activation	MAP	AvgRec	MRR	P	R	F_1	Acc
PV-DBOW	SGD	relu	**0.7306**	0.8416	79.61	0.6607	0.5786	0.6169	0.708
PV-DBOW	SGD	tanh	0.7188	0.8343	79.11	0.6684	0.5658	0.6129	0.7095
PV-DBOW	SGD	logistic	0.7179	0.8346	79.13	0.6652	0.553	0.6039	0.7052
PV-DBOW	Adam	logistic	0.7177	0.8342	78.96	0.6635	0.5726	0.6147	0.7083
PV-DBOW	Adam	tanh	0.7169	0.8339	78.64	0.655	0.5771	0.6136	0.7046
PV-DBOW	Adam	relu	0.7161	0.8263	79.45	0.6298	0.6005	0.6148	0.6942

TABLE 5: Experiments using (q, c, avg_com_q) inputs – Best results

Clearly there is a significant improvement in MAP scores after inclusion of the centroidal comment for each question as an input feature. Further experiments thus is done inclusive of avg_com_q in the input tuple.

4.3.2.3 Further improvement with Syntactic and Metadata Features

Finally, we experimented by including a few more features as described in subsection 3.3.2; which includes various thread level metadata features, and features that capture syntactic similarities between the question and comment text. The best results are tabulated in Table 6. Complete results are tabulated under Appendix D. Further, we excluded the *ADAM* solver from parameters, as *SGD* performs significantly better on all runs (can be seen from Table 5 as well).

Category	Solver	Activation	MAP	AvgRec	MRR	P	R	F_1	Acc
PV-DBOW	SGD	tanh	**0.7774**	0.882	85.58	0.7081	0.6351	0.6696	0.7453
PV-DBOW	SGD	relu	0.7743	0.8796	84.81	0.7057	0.626	0.6635	0.7419
PV-DBOW	SGD	logistic	0.7726	0.8787	85.51	0.7149	0.6358	0.673	0.7489

TABLE 6: Experiments using $(q, c, avg\_com_q, ft_{(q,c)})$ inputs – Best results

Conclusions

Appendix A

Training PV-DM and PV-DBOW

Category	Window Size	Epochs	Normalized Sq. Error (A)	Norm. Sq. Error (Random) (B)	Ratio (B/A)
PV-DBOW	10	5	0.14	0.80	5.89
PV-DBOW	10	10	0.14	0.83	5.84
PV-DBOW	15	5	0.15	0.80	5.50
PV-DBOW	10	3	0.14	0.78	5.48
PV-DBOW	15	10	0.15	0.82	5.47
PV-DBOW	15	3	0.15	0.78	5.12
PV-DBOW	20	5	0.16	0.80	5.09
PV-DBOW	20	10	0.16	0.82	5.04
PV-DBOW	20	3	0.16	0.77	4.71
PV-DM	10	5	0.21	0.99	4.67
PV-DM	15	10	0.22	0.98	4.47
PV-DM	15	5	0.23	0.98	4.29
PV-DM	20	10	0.23	0.98	4.28
PV-DM	25	10	0.24	0.98	4.17
PV-DM	20	5	0.24	0.98	4.09
PV-DM	15	20	0.24	0.98	4.03
PV-DM	25	5	0.25	0.98	3.95
PV-DM	20	20	0.25	0.98	3.95
PV-DM	25	20	0.25	0.98	3.89
PV-DBOW	10	1	0.19	0.73	3.75
PV-DM	15	30	0.26	0.96	3.69
PV-DM	20	30	0.27	0.97	3.64
PV-DM	25	30	0.27	0.97	3.60
PV-DBOW	15	1	0.21	0.72	3.48
PV-DBOW	20	1	0.22	0.72	3.23
PV-DM	10	1	0.33	0.98	2.94
PV-DM	15	1	0.36	0.97	2.72
PV-DM	20	1	0.37	0.97	2.59
PV-DM	25	1	0.38	0.97	2.52

Table 7: Training document vector representations PV-DM and PV-DBOW – All results

Dimension	**Window Size**	**Epochs**	**Normalized Sq. Error (A)**	**Norm. Sq. Error (Random) (B)**	**Ratio (B/A)**
100	10	5	0.14	0.80	5.89
100	10	10	0.14	0.83	5.84
200	10	10	0.15	0.84	5.65
100	15	5	0.15	0.80	5.50
100	10	3	0.14	0.78	5.48
200	10	5	0.15	0.82	5.47
100	15	10	0.15	0.82	5.47
200	15	10	0.16	0.84	5.18
100	15	3	0.15	0.78	5.12
100	20	5	0.16	0.80	5.09
100	20	10	0.16	0.82	5.04
200	15	5	0.16	0.82	5.01
200	10	3	0.16	0.80	4.96
100	20	3	0.16	0.77	4.71
200	20	10	0.18	0.84	4.71
200	20	5	0.18	0.82	4.58
200	15	3	0.18	0.80	4.54
200	20	3	0.19	0.79	4.17
100	10	1	0.19	0.73	3.75
100	15	1	0.21	0.72	3.48
200	10	1	0.23	0.76	3.33
100	20	1	0.22	0.72	3.23
200	15	1	0.24	0.75	3.06
200	20	1	0.26	0.74	2.86

TABLE 8: Training PV-DBOW document vectors of sizes 100 and 200 – All results

Appendix B

Preliminary experiments

Category	**Solver**	**Activation**	**Hidden Layer**	**MAP**	**AvgRec**	**MRR**	**P**	**R**	**F_1**	**Acc**
PV-DBOW	Adam	logistic	[500, 250, -]	0.7049	0.8292	77.62	0.6601	0.5508	0.6005	0.7021
PV-DBOW	SGD	relu	[100, -, -]	0.7019	0.8251	77.16	0.6327	0.5937	0.6126	0.6948
PV-DBOW	SGD	logistic	[50, -, -]	0.7018	0.8242	77.32	0.6412	0.5877	0.6133	0.6988
PV-DBOW	SGD	logistic	[100, -, -]	0.7013	0.8242	77.23	0.6353	0.5884	0.6109	0.6954
PV-DBOW	SGD	tanh	[500, 100, 100]	0.7009	0.8245	76.62	0.6339	0.5914	0.6119	0.6951
PV-DBOW	Adam	logistic	[50, 50, 50]	0.7008	0.8252	76.8	0.6043	0.6584	0.6302	0.6859
PV-DBOW	SGD	relu	[50, -, -]	0.7007	0.824	77.01	0.6374	0.5899	0.6127	0.6969
PV-DBOW	SGD	tanh	[250, 100, -]	0.7007	0.8237	76.86	0.631	0.5854	0.6073	0.6924
PV-DBOW	Adam	logistic	[100, 50, 50]	0.7007	0.8251	76.89	0.6325	0.5997	0.6157	0.6957
PV-DBOW	SGD	logistic	[250, -, -]	0.7006	0.8236	77.36	0.6396	0.5862	0.6117	0.6976
PV-DBOW	Adam	logistic	[100, 100, 100]	0.7006	0.825	76.9	0.6404	0.5749	0.6059	0.696
PV-DBOW	SGD	logistic	[500, -, -]	0.7005	0.824	77.2	0.6369	0.5847	0.6097	0.6957
PV-DBOW	SGD	tanh	[250, 50, 50]	0.7004	0.8241	76.89	0.6339	0.5914	0.6119	0.6951
PV-DBOW	Adam	logistic	[250, 250, 250]	0.7003	0.8248	76.97	0.6217	0.6245	0.6231	0.693
PV-DBOW	Adam	logistic	[250, 250, 50]	0.7	0.8248	76.94	0.6205	0.62	0.6202	0.6914
PV-DBOW	Adam	logistic	[500, 100, -]	0.6999	0.8244	76.92	0.6281	0.6087	0.6183	0.6945
PV-DBOW	Adam	logistic	[250, 100, -]	0.6998	0.824	76.7	0.6164	0.6275	0.6219	0.6899
PV-DBOW	Adam	logistic	[250, 50, -]	0.6998	0.8239	76.66	0.6194	0.6381	0.6286	0.6936
PV-DBOW	Adam	logistic	[500, 50, -]	0.6997	0.8243	76.75	0.6346	0.605	0.6194	0.6979
PV-DBOW	Adam	logistic	[250, 250, 100]	0.6997	0.8243	76.84	0.6343	0.5899	0.6113	0.6951
PV-DBOW	SGD	tanh	[250, 100, 50]	0.6996	0.8235	76.66	0.6334	0.5877	0.6097	0.6942
PV-DBOW	SGD	tanh	[100, 100, 50]	0.6996	0.8237	76.99	0.637	0.5877	0.6114	0.6963
PV-DBOW	SGD	tanh	[100, -, -]	0.6996	0.823	76.67	0.634	0.5839	0.6079	0.6939
PV-DBOW	Adam	logistic	[500, 250, 50]	0.6995	0.8238	76.69	0.6447	0.5749	0.6078	0.6985
PV-DBOW	SGD	tanh	[500, 500, 250]	0.6994	0.8241	76.76	0.6339	0.5914	0.6119	0.6951
PV-DBOW	SGD	tanh	[500, 500, 100]	0.6994	0.8235	76.89	0.6347	0.5884	0.6107	0.6951
PV-DBOW	SGD	tanh	[500, 500, -]	0.6994	0.8238	76.43	0.6347	0.5884	0.6107	0.6951
PV-DBOW	Adam	logistic	[100, 100, 50]	0.6994	0.824	76.51	0.6406	0.5794	0.6085	0.6969
PV-DBOW	Adam	logistic	[100, 50, -]	0.6994	0.8243	76.74	0.6279	0.6095	0.6186	0.6945
PV-DBOW	Adam	relu	[500, 50, -]	0.6993	0.8106	76.94	0.5998	0.5741	0.5867	0.6713
PV-DBOW	SGD	tanh	[500, 500, 50]	0.6992	0.8236	76.5	0.6344	0.5914	0.6121	0.6954

TABLE 9: Preliminary experiments using only (q, c) inputs – All results (MAP>0.6).

Category	**Solver**	**Activation**	**Hidden Layer**	**MAP**	**AvgRec**	**MRR**	**P**	**R**	$\mathbf{F_1}$	**Acc**
PV-DBOW	SGD	tanh	[250, 50, -]	0.6992	0.8225	76.76	0.633	0.5892	0.6103	0.6942
PV-DBOW	SGD	tanh	[100, 100, -]	0.6992	0.8241	76.74	0.6349	0.5862	0.6095	0.6948
PV-DBOW	Adam	logistic	[500, 500, 500]	0.6992	0.8246	76.77	0.6098	0.6584	0.6331	0.6899
PV-DBOW	Adam	logistic	[250, 100, 50]	0.6992	0.8238	76.74	0.6224	0.6275	0.625	0.6939
PV-DBOW	Adam	logistic	[50, 50, -]	0.6992	0.8241	76.87	0.6333	0.6042	0.6184	0.6969
PV-DBOW	SGD	tanh	[50, 50, -]	0.699	0.8236	76.77	0.6373	0.5884	0.6119	0.6966
PV-DBOW	SGD	tanh	[50, -, -]	0.699	0.8235	76.95	0.6407	0.5877	0.613	0.6985
PV-DBOW	SGD	relu	[500, -, -]	0.6989	0.824	76.58	0.6377	0.5907	0.6133	0.6972
PV-DBOW	SGD	tanh	[500, 100, -]	0.6989	0.8231	76.79	0.6338	0.5862	0.6091	0.6942
PV-DBOW	SGD	tanh	[250, -, -]	0.6987	0.8238	76.94	0.6321	0.5869	0.6087	0.6933
PV-DBOW	SGD	tanh	[100, 100, 100]	0.6987	0.8235	76.59	0.6365	0.5877	0.6111	0.696
PV-DBOW	SGD	tanh	[500, 100, 50]	0.6986	0.8233	76.5	0.6365	0.5929	0.6139	0.6969
PV-DBOW	Adam	logistic	[100, 100, -]	0.6986	0.8235	76.28	0.6192	0.6253	0.6222	0.6914
PV-DBOW	SGD	relu	[250, -, -]	0.6985	0.824	76.55	0.6369	0.5899	0.6125	0.6966
PV-DBOW	Adam	logistic	[100, -, -]	0.6984	0.8232	76.54	0.643	0.5666	0.6024	0.696
PV-DBOW	SGD	tanh	[500, 250, 100]	0.6983	0.8233	76.2	0.6356	0.5907	0.6123	0.696
PV-DBOW	SGD	tanh	[500, 250, 50]	0.6983	0.8229	76.52	0.635	0.5929	0.6132	0.696
PV-DBOW	SGD	tanh	[500, 250, -]	0.6983	0.8235	76.68	0.6339	0.5877	0.6099	0.6945
PV-DBOW	Adam	logistic	[500, -, -]	0.6983	0.823	76.51	0.5983	0.6892	0.6406	0.6856
PV-DBOW	Adam	logistic	[50, -, -]	0.6983	0.8233	76.55	0.6385	0.5847	0.6104	0.6966
PV-DBOW	SGD	tanh	[500, 250, 250]	0.6982	0.8234	76.61	0.6341	0.5869	0.6096	0.6945
PV-DBOW	SGD	tanh	[500, 50, 50]	0.6982	0.8232	76.63	0.6309	0.5892	0.6093	0.693
PV-DBOW	SGD	tanh	[500, -, -]	0.6982	0.8235	76.68	0.6339	0.5824	0.6071	0.6936
PV-DBOW	Adam	logistic	[500, 500, 50]	0.6982	0.8211	76.28	0.6311	0.5869	0.6082	0.6927
PV-DBOW	Adam	logistic	[250, 250, -]	0.6981	0.8229	76.51	0.6149	0.6441	0.6292	0.6914
PV-DBOW	Adam	tanh	[100, -, -]	0.698	0.8231	76.35	0.6386	0.5546	0.5936	0.6914
PV-DBOW	Adam	tanh	[50, -, -]	0.698	0.8232	76.64	0.6264	0.617	0.6217	0.6948
PV-DBOW	SGD	tanh	[500, 50, -]	0.6979	0.8229	76.37	0.6338	0.5899	0.6111	0.6948
PV-DBOW	SGD	tanh	[100, 50, 50]	0.6979	0.8239	76.52	0.6339	0.5877	0.6099	0.6945
PV-DBOW	SGD	tanh	[250, 250, 50]	0.6975	0.8222	76.47	0.6316	0.5869	0.6084	0.693
PV-DBOW	SGD	tanh	[50, 50, 50]	0.6975	0.8224	76.66	0.6369	0.5899	0.6125	0.6966
PV-DBOW	SGD	tanh	[250, 250, 100]	0.6974	0.8232	76.6	0.6323	0.5899	0.6104	0.6939
PV-DBOW	SGD	tanh	[250, 250, -]	0.6974	0.8224	76.32	0.633	0.5854	0.6083	0.6936
PV-DBOW	SGD	tanh	[250, 100, 100]	0.6974	0.8228	76.39	0.6322	0.5884	0.6095	0.6936
PV-DBOW	Adam	tanh	[500, -, -]	0.6974	0.8228	76.48	0.6274	0.6245	0.6259	0.6966
PV-DBOW	SGD	tanh	[100, 50, -]	0.6973	0.8231	76.44	0.6356	0.5892	0.6115	0.6957
PV-DBOW	SGD	tanh	[500, 500, 500]	0.6971	0.8221	76.48	0.6331	0.5907	0.6111	0.6945
PV-DBOW	Adam	logistic	[250, -, -]	0.6966	0.822	76.19	0.647	0.553	0.5963	0.6957
PV-DBOW	Adam	tanh	[250, -, -]	0.6964	0.8218	76.23	0.6331	0.5869	0.6091	0.6939
PV-DBOW	SGD	tanh	[250, 250, 250]	0.6962	0.8214	76.16	0.6335	0.5892	0.6105	0.6945
PV-DBOW	Adam	logistic	[500, 250, 250]	0.6959	0.8205	76.23	0.6296	0.6087	0.619	0.6954
PV-DBOW	Adam	relu	[500, 500, 500]	0.6953	0.8134	75.64	0.5863	0.6185	0.602	0.6676
PV-DBOW	Adam	logistic	[500, 250, 100]	0.6952	0.8195	75.94	0.6439	0.5538	0.5955	0.6942
PV-DBOW	Adam	logistic	[500, 500, 100]	0.6948	0.8196	76.16	0.6254	0.6193	0.6223	0.6945
PV-DBOW	Adam	logistic	[500, 500, -]	0.6948	0.8206	75.89	0.6493	0.5433	0.5916	0.6951
PV-DBOW	Adam	logistic	[500, 100, 100]	0.6944	0.82	75.84	0.6271	0.605	0.6159	0.6933
PV-DBOW	Adam	logistic	[500, 100, 50]	0.6938	0.8192	76	0.6271	0.6035	0.615	0.693
PV-DBOW	Adam	logistic	[250, 100, 100]	0.6931	0.8187	75.65	0.6536	0.5252	0.5824	0.6939
PV-DBOW	Adam	logistic	[250, 50, 50]	0.693	0.8196	75.76	0.6325	0.5997	0.6157	0.6957
PV-DBOW	Adam	logistic	[500, 500, 250]	0.6927	0.8189	75.7	0.5982	0.6855	0.6388	0.685
PV-DBOW	Adam	logistic	[500, 50, 50]	0.6919	0.8187	75.65	0.6285	0.6035	0.6157	0.6939
PV-DBOW	SGD	relu	[500, 500, 100]	0.6898	0.8095	76.17	0.5901	0.5839	0.587	0.6661
PV-DBOW	Adam	relu	[500, 500, 100]	0.689	0.8085	76.14	0.5895	0.5726	0.5809	0.6642
PV-DBOW	Adam	relu	[500, 250, 50]	0.6889	0.8052	77.5	0.5756	0.5613	0.5684	0.6535
PV-DBOW	Adam	relu	[500, 100, -]	0.688	0.8094	75.7	0.5912	0.5636	0.577	0.6642
PV-DBOW	Adam	relu	[500, 250, 250]	0.6872	0.81	75.47	0.5879	0.6193	0.6032	0.6688
PV-DBOW	Adam	relu	[500, -, -]	0.6871	0.8081	76.88	0.5729	0.5824	0.5776	0.6538
PV-DBOW	SGD	relu	[500, 100, 100]	0.6861	0.8071	77.62	0.577	0.5666	0.5718	0.655

Preliminary experiments using only (q, c) inputs – All results (MAP>0.6).

Category	Solver	Activation	Hidden Layer	MAP	AvgRec	MRR	P	R	F_1	Acc
PV-DBOW	Adam	relu	[250, -, -]	0.6861	0.8053	75.89	0.5904	0.5553	0.5723	0.6627
PV-DBOW	SGD	relu	[500, 250, -]	0.6855	0.8081	76.23	0.585	0.5515	0.5678	0.6587
PV-DBOW	SGD	relu	[500, 100, -]	0.6853	0.8042	77.34	0.5876	0.5553	0.571	0.6609
PV-DBOW	SGD	relu	[500, 500, -]	0.6845	0.8052	75.42	0.587	0.5636	0.575	0.6615
PV-DBOW	SGD	relu	[500, 250, 100]	0.6828	0.8012	75.33	0.5753	0.5719	0.5736	0.6544
PV-DBOW	SGD	relu	[500, 50, -]	0.6823	0.8055	75.46	0.5771	0.5719	0.5745	0.6557
PV-DBOW	Adam	relu	[250, 250, 100]	0.6823	0.8151	76.37	0.6077	0.5094	0.5542	0.667
PV-DBOW	Adam	relu	[250, 250, 250]	0.6816	0.8073	76.21	0.6163	0.4786	0.5388	0.667
PV-DBOW	SGD	relu	[500, 250, 250]	0.6805	0.8013	75.65	0.5747	0.5704	0.5725	0.6538
PV-DBOW	Adam	relu	[500, 500, 250]	0.68	0.8035	76.37	0.6021	0.5613	0.581	0.6709
PV-DBOW	Adam	relu	[500, 250, 100]	0.6796	0.7963	75.73	0.5829	0.611	0.5966	0.6642
PV-DBOW	Adam	relu	[500, 100, 50]	0.6795	0.8025	75.87	0.5899	0.5899	0.5899	0.6667
PV-DBOW	SGD	relu	[500, 250, 50]	0.679	0.8	74.37	0.5847	0.5636	0.5739	0.6599
PV-DBOW	Adam	relu	[50, -, -]	0.6789	0.802	74.61	0.5746	0.5388	0.5561	0.6505
PV-DBOW	Adam	relu	[500, 250, -]	0.6784	0.8015	74.97	0.6037	0.5388	0.5694	0.6688
PV-DBOW	Adam	relu	[250, 250, 50]	0.6784	0.8029	74.02	0.5892	0.5192	0.552	0.6575
PV-DBOW	SGD	relu	[500, 100, 50]	0.678	0.8027	75.18	0.5828	0.5771	0.58	0.6602
PV-DBOW	Adam	relu	[250, 50, -]	0.678	0.8043	74.84	0.5899	0.5335	0.5603	0.6596
PV-DBOW	Adam	relu	[500, 500, 50]	0.6779	0.7993	75.16	0.6069	0.5192	0.5596	0.6679
PV-DBOW	Adam	relu	[250, 50, 50]	0.6777	0.8028	74.79	0.6144	0.5011	0.552	0.6694
PV-DBOW	Adam	relu	[100, -, -]	0.6764	0.7963	75.58	0.5776	0.5628	0.5701	0.655
PV-DBOW	Adam	relu	[250, 100, 50]	0.6759	0.8006	75.18	0.5827	0.5222	0.5508	0.6538
PV-DBOW	SGD	relu	[500, 500, 500]	0.6757	0.7998	74.65	0.582	0.5658	0.5738	0.6584
PV-DBOW	SGD	relu	[500, 500, 50]	0.675	0.8002	75.24	0.5778	0.5643	0.571	0.6554
PV-DBOW	Adam	relu	[250, 100, 100]	0.6749	0.8009	75.43	0.5714	0.626	0.5975	0.6572
PV-DBOW	Adam	relu	[500, 50, 50]	0.6745	0.798	73.88	0.5675	0.6328	0.5984	0.6547
PV-DBOW	Adam	relu	[100, 100, -]	0.6736	0.7985	73.98	0.5734	0.5816	0.5775	0.6541
PV-DBOW	SGD	relu	[500, 50, 50]	0.6735	0.7994	75.36	0.5847	0.5847	0.5847	0.6624
PV-DBOW	SGD	relu	[50, 50, -]	0.6731	0.7978	74.39	0.5764	0.5621	0.5691	0.6541
PV-DBOW	SGD	relu	[250, 250, 50]	0.6726	0.7935	73.95	0.5671	0.5598	0.5634	0.6474
PV-DBOW	Adam	tanh	[500, 500, 500]	0.6724	0.7953	75.14	0.5931	0.5824	0.5877	0.6679
PV-DBOW	SGD	relu	[500, 500, 250]	0.6723	0.7955	73.58	0.5784	0.5636	0.5709	0.6557
PV-DBOW	SGD	relu	[250, 250, 100]	0.6721	0.7967	75.01	0.5756	0.5643	0.5699	0.6538
PV-DBOW	SGD	relu	[250, 100, -]	0.6707	0.7989	74.35	0.5655	0.5327	0.5486	0.6437
PV-DBOW	Adam	relu	[500, 500, -]	0.6707	0.7923	73.13	0.5747	0.5786	0.5767	0.6547
PV-DBOW	SGD	relu	[50, 50, 50]	0.67	0.8021	74.36	0.5796	0.5997	0.5895	0.6606
PV-DBOW	SGD	relu	[250, 250, -]	0.6693	0.7942	74.6	0.578	0.5523	0.5648	0.6541
PV-DBOW	SGD	relu	[250, 100, 50]	0.6685	0.7909	73.52	0.5592	0.547	0.5531	0.6407
PV-DBOW	Adam	relu	[250, 250, -]	0.6684	0.8003	73.9	0.5709	0.5756	0.5732	0.6517
PV-DBOW	SGD	relu	[250, 50, 50]	0.668	0.7915	73.88	0.5735	0.5666	0.57	0.6526
PV-DBOW	Adam	relu	[250, 100, -]	0.6673	0.7936	73.37	0.5725	0.5764	0.5744	0.6529
PV-DBOW	Adam	tanh	[500, 500, 250]	0.6658	0.7878	73.56	0.5874	0.5764	0.5818	0.6633
PV-DBOW	Adam	tanh	[500, 250, 100]	0.6652	0.7888	72.88	0.5847	0.5508	0.5672	0.6584
PV-DBOW	Adam	relu	[500, 100, 100]	0.6651	0.7938	72.41	0.5822	0.6102	0.5959	0.6636
PV-DBOW	Adam	relu	[50, 50, -]	0.6643	0.7886	73.6	0.5562	0.5583	0.5573	0.6394
PV-DBOW	SGD	relu	[250, 100, 100]	0.6642	0.7908	73.86	0.5731	0.5455	0.559	0.6502
PV-DBOW	SGD	relu	[100, 50, -]	0.664	0.7927	74.39	0.5575	0.5688	0.5631	0.6413
PV-DBOW	SGD	relu	[250, 50, -]	0.6629	0.7963	73.97	0.5704	0.5455	0.5577	0.6483
PV-DBOW	SGD	relu	[250, 250, 250]	0.6627	0.7916	72.39	0.5732	0.5365	0.5542	0.6492
PV-DBOW	Adam	tanh	[500, 500, 100]	0.662	0.789	73.43	0.5696	0.5786	0.5741	0.6511
PV-DBOW	Adam	tanh	[250, 250, 250]	0.6615	0.7823	73.69	0.5816	0.5628	0.5721	0.6578
PV-DBOW	Adam	tanh	[500, 500, -]	0.6602	0.7872	74.35	0.5988	0.5816	0.5901	0.6716
PV-DBOW	Adam	tanh	[250, 250, 100]	0.6601	0.7876	72.89	0.5831	0.5598	0.5712	0.6584
PV-DBOW	Adam	relu	[100, 50, -]	0.6596	0.7862	74.06	0.5573	0.5455	0.5513	0.6391
PV-DBOW	Adam	tanh	[500, 250, 50]	0.6582	0.7858	72.06	0.6067	0.5606	0.5827	0.6737
PV-DBOW	SGD	relu	[100, 100, -]	0.6581	0.7863	72.44	0.5478	0.5515	0.5497	0.6327
PV-DBOW	SGD	relu	[100, 50, 50]	0.6581	0.787	72.68	0.5545	0.5591	0.5568	0.6382
PV-DM	SGD	relu	[100, -, -]	0.6578	0.7855	74.58	0.5793	0.5357	0.5567	0.6532

Preliminary experiments using only (q, c) inputs – All results (MAP>0.6).

Category	**Solver**	**Activation**	**Hidden Layer**	**MAP**	**AvgRec**	**MRR**	**P**	**R**	**F_1**	**Acc**
PV-DBOW	Adam	tanh	[250, 50, -]	0.6574	0.7864	72.75	0.5678	0.5922	0.5797	0.6511
PV-DBOW	Adam	tanh	[500, 500, 50]	0.6572	0.7909	72.68	0.5879	0.5862	0.587	0.6648
PV-DM	SGD	relu	[50, -, -]	0.6566	0.7812	74.01	0.5468	0.5139	0.5299	0.6294
PV-DBOW	Adam	tanh	[500, 50, -]	0.6556	0.784	73.92	0.5698	0.5741	0.572	0.6508
PV-DBOW	Adam	tanh	[500, 250, 250]	0.655	0.7826	73.79	0.5745	0.5922	0.5832	0.656
PV-DBOW	Adam	relu	[100, 100, 100]	0.6544	0.7836	72.81	0.5582	0.5591	0.5586	0.641
PV-DBOW	SGD	relu	[100, 100, 100]	0.6542	0.7831	73.9	0.5391	0.5553	0.5471	0.6263
PV-DBOW	Adam	tanh	[100, 100, 50]	0.6532	0.782	73.38	0.5583	0.5583	0.5583	0.641
PV-DBOW	Adam	tanh	[250, 250, 50]	0.653	0.7853	74.63	0.5734	0.5553	0.5642	0.6514
PV-DBOW	SGD	relu	[100, 100, 50]	0.6527	0.7798	72.78	0.5398	0.5508	0.5453	0.6266
PV-DM	SGD	relu	[250, -, -]	0.651	0.7788	72.85	0.5512	0.5019	0.5254	0.6315
PV-DBOW	Adam	tanh	[100, 50, 50]	0.65	0.779	71.93	0.565	0.5726	0.5688	0.6471
PV-DBOW	Adam	tanh	[500, 100, 100]	0.6497	0.7739	71.12	0.5695	0.5764	0.5729	0.6508
PV-DM	SGD	relu	[500, -, -]	0.6489	0.7816	73.25	0.5672	0.5719	0.5695	0.6486
PV-DBOW	Adam	tanh	[250, 100, -]	0.6483	0.7797	72.33	0.5628	0.5801	0.5713	0.6462
PV-DBOW	Adam	tanh	[250, 100, 50]	0.6455	0.7772	70.64	0.5734	0.5493	0.5611	0.6508
PV-DBOW	Adam	tanh	[250, 100, 100]	0.6433	0.7745	71.85	0.5766	0.5944	0.5854	0.6578
PV-DBOW	Adam	tanh	[500, 250, -]	0.6432	0.7718	72.2	0.543	0.5651	0.5538	0.63
PV-DBOW	Adam	relu	[100, 100, 50]	0.6431	0.7801	72.71	0.5613	0.5613	0.5613	0.6434
PV-DBOW	Adam	tanh	[100, 100, -]	0.643	0.7732	71.16	0.5537	0.5741	0.5637	0.6388
PV-DBOW	Adam	tanh	[500, 100, 50]	0.6416	0.7717	71.75	0.5449	0.5388	0.5418	0.6297
PV-DBOW	Adam	tanh	[100, 100, 100]	0.6414	0.7705	71.56	0.5532	0.5282	0.5404	0.6349
PV-DBOW	Adam	tanh	[100, 50, -]	0.6413	0.7726	72.96	0.5376	0.5591	0.5481	0.6254
PV-DBOW	Adam	tanh	[500, 100, -]	0.6397	0.7683	70.39	0.566	0.5485	0.5571	0.6456
PV-DBOW	Adam	tanh	[50, 50, -]	0.6376	0.7578	70.44	0.5467	0.5636	0.555	0.6327
PV-DBOW	Adam	relu	[100, 50, 50]	0.6364	0.7727	70.43	0.5684	0.6095	0.5882	0.6532
PV-DBOW	Adam	tanh	[500, 50, 50]	0.6358	0.7675	70.43	0.5545	0.5515	0.553	0.6376
PV-DBOW	Adam	tanh	[250, 250, -]	0.6347	0.7682	70.07	0.5676	0.5719	0.5697	0.6489
PV-DM	SGD	relu	[50, 50, -]	0.6345	0.7582	72.47	0.5159	0.5132	0.5145	0.6064
PV-DBOW	Adam	relu	[50, 50, 50]	0.6333	0.7639	70.17	0.5441	0.5613	0.5526	0.6306
PV-DBOW	Adam	tanh	[50, 50, 50]	0.631	0.7669	70.62	0.5428	0.5636	0.553	0.6297
PV-DBOW	Adam	tanh	[250, 50, 50]	0.6292	0.7619	70.82	0.5508	0.5591	0.5549	0.6355
PV-DM	SGD	relu	[500, 250, 50]	0.6286	0.7586	72.08	0.5227	0.5546	0.5382	0.6131
PV-DM	SGD	relu	[500, 500, 250]	0.6237	0.7542	71.01	0.5135	0.544	0.5283	0.6052
PV-DM	SGD	relu	[500, 100, 100]	0.6235	0.7531	71.02	0.5145	0.547	0.5303	0.6061
PV-DM	SGD	relu	[500, 50, -]	0.6215	0.756	70.78	0.5138	0.5613	0.5365	0.6058
PV-DM	SGD	relu	[500, 500, 500]	0.6204	0.754	71.33	0.4986	0.5252	0.5115	0.5924
PV-DM	SGD	relu	[500, 100, 50]	0.6194	0.7524	70.9	0.5223	0.538	0.53	0.6122
PV-DM	SGD	relu	[500, 250, 100]	0.6193	0.7517	70.47	0.5032	0.532	0.5172	0.5963
PV-DM	SGD	relu	[500, 500, 100]	0.6192	0.7505	70.94	0.5158	0.529	0.5223	0.6067
PV-DM	SGD	relu	[500, 100, -]	0.6184	0.7496	70.66	0.5207	0.5485	0.5343	0.6113
PV-DM	SGD	relu	[500, 500, -]	0.6175	0.7533	70.17	0.513	0.5485	0.5302	0.6049
PV-DM	SGD	relu	[500, 500, 50]	0.6174	0.7525	71.03	0.5246	0.5613	0.5423	0.615
PV-DM	SGD	relu	[250, 250, -]	0.6168	0.7424	70.98	0.4877	0.553	0.5183	0.5823
PV-DM	SGD	relu	[500, 250, 250]	0.6166	0.7523	71.18	0.5228	0.535	0.5288	0.6125
PV-DM	SGD	relu	[500, 250, -]	0.6164	0.7513	70.24	0.5217	0.5598	0.5401	0.6125
PV-DM	SGD	relu	[500, 50, 50]	0.6161	0.7498	69.61	0.5162	0.5388	0.5272	0.6073
PV-DM	SGD	relu	[250, 50, -]	0.6154	0.7413	72.24	0.51	0.5546	0.5314	0.6024
PV-DM	SGD	relu	[250, 250, 50]	0.6146	0.7442	69.09	0.478	0.5305	0.5029	0.5737
PV-DM	SGD	relu	[100, 50, 50]	0.6131	0.7449	69.56	0.5068	0.5598	0.532	0.5997
PV-DM	SGD	relu	[250, 50, 50]	0.6128	0.7386	69.05	0.4951	0.5357	0.5146	0.5893
PV-DM	SGD	relu	[100, 50, -]	0.6108	0.7475	69.63	0.498	0.553	0.5241	0.5917
PV-DM	SGD	relu	[250, 100, -]	0.6093	0.7437	68.79	0.5153	0.5583	0.5359	0.607
PV-DM	SGD	relu	[100, 100, -]	0.6089	0.7471	68.59	0.5058	0.5869	0.5434	0.5991
PV-DM	SGD	relu	[250, 100, 100]	0.6077	0.7405	69.81	0.51	0.5365	0.5229	0.6021
PV-DM	SGD	relu	[250, 250, 100]	0.6047	0.7417	68.62	0.5048	0.5553	0.5288	0.5979
PV-DM	SGD	relu	[50, 50, 50]	0.6009	0.7415	68.04	0.5065	0.5862	0.5434	0.5997

Preliminary experiments using only (q, c) inputs – All results (MAP>0.6).

Appendix C

Experiments post inclusion of Average Answer

Category	Solver	Activation	Hidden Layer	MAP	AvgRec	MRR	P	R	F_1	Acc
PV-DBOW	SGD	relu	[250, -, -]	0.7306	0.8416	79.61	0.6607	0.5786	0.6169	0.708
PV-DBOW	SGD	relu	[100, -, -]	0.7296	0.8418	80.81	0.6678	0.5688	0.6144	0.7098
PV-DBOW	SGD	relu	[500, -, -]	0.7253	0.8429	78.88	0.6536	0.6035	0.6275	0.7089
PV-DBOW	SGD	tanh	[500, 100, -]	0.7188	0.8343	79.11	0.6684	0.5658	0.6129	0.7095
PV-DBOW	SGD	tanh	[250, 250, 250]	0.7182	0.834	78.87	0.6655	0.5658	0.6116	0.708
PV-DBOW	SGD	logistic	[100, -, -]	0.7179	0.8346	79.13	0.6652	0.553	0.6039	0.7052
PV-DBOW	Adam	logistic	[50, -, -]	0.7177	0.8342	78.96	0.6635	0.5726	0.6147	0.7083
PV-DBOW	SGD	tanh	[500, 500, 500]	0.7172	0.8337	78.78	0.6675	0.5696	0.6147	0.7098
PV-DBOW	SGD	tanh	[250, 100, 50]	0.7171	0.8329	78.48	0.6655	0.5673	0.6125	0.7083
PV-DBOW	SGD	tanh	[50, -, -]	0.7171	0.8339	79.09	0.6628	0.5606	0.6074	0.7055
PV-DBOW	SGD	tanh	[250, 250, 100]	0.7169	0.8333	78.79	0.6661	0.5613	0.6092	0.7073
PV-DBOW	SGD	tanh	[100, 100, -]	0.7169	0.8338	79.13	0.6652	0.5576	0.6066	0.7061
PV-DBOW	SGD	tanh	[50, 50, 50]	0.7169	0.8325	78.47	0.6673	0.5658	0.6124	0.7089
PV-DBOW	Adam	tanh	[250, -, -]	0.7169	0.8339	78.64	0.655	0.5771	0.6136	0.7046
PV-DBOW	SGD	logistic	[250, -, -]	0.7168	0.8338	78.83	0.6664	0.5576	0.6071	0.7067
PV-DBOW	SGD	tanh	[100, 50, 50]	0.7167	0.8326	78.84	0.6687	0.5636	0.6117	0.7092
PV-DBOW	Adam	logistic	[250, -, -]	0.7167	0.834	78.68	0.6676	0.538	0.5958	0.7034
PV-DBOW	SGD	tanh	[500, 500, 50]	0.7166	0.8333	78.75	0.6676	0.5681	0.6138	0.7095
PV-DBOW	SGD	tanh	[250, -, -]	0.7166	0.8336	79.01	0.6649	0.5598	0.6078	0.7064
PV-DBOW	SGD	tanh	[250, 250, 50]	0.7165	0.8333	78.64	0.6652	0.5621	0.6093	0.707
PV-DBOW	SGD	tanh	[250, 250, -]	0.7165	0.8324	78.77	0.6661	0.5628	0.6101	0.7076
PV-DBOW	SGD	tanh	[100, 100, 100]	0.7164	0.8328	78.71	0.6667	0.5658	0.6121	0.7086
PV-DBOW	Adam	logistic	[250, 250, -]	0.7164	0.8334	78.65	0.6562	0.5959	0.6246	0.7089
PV-DBOW	Adam	logistic	[100, 100, -]	0.7163	0.8331	78.76	0.6598	0.5779	0.6161	0.7073
PV-DBOW	SGD	logistic	[500, -, -]	0.7162	0.8336	78.93	0.6634	0.553	0.6032	0.7043
PV-DBOW	Adam	logistic	[500, -, -]	0.7162	0.8334	78.79	0.6603	0.5704	0.612	0.7061
PV-DBOW	Adam	logistic	[100, 100, 50]	0.7162	0.8331	78.73	0.6519	0.5862	0.6173	0.7046
PV-DBOW	SGD	tanh	[500, 250, 50]	0.7161	0.8332	78.96	0.667	0.5621	0.61	0.708
PV-DBOW	SGD	tanh	[250, 50, -]	0.7161	0.8335	78.69	0.6602	0.5613	0.6068	0.7043
PV-DBOW	Adam	relu	[500, 250, 250]	0.7161	0.8263	79.45	0.6298	0.6005	0.6148	0.6942

TABLE 10: Experiments using (q, c, avg_com_q) inputs – All results (MAP>0.6).

Category	**Solver**	**Activation**	**Hidden Layer**	**MAP**	**AvgRec**	**MRR**	**P**	**R**	$\mathbf{F_1}$	**Acc**
PV-DBOW	SGD	tanh	[250, 100, -]	0.716	0.8328	78.31	0.6655	0.5628	0.6099	0.7073
PV-DBOW	SGD	tanh	[500, 500, -]	0.7158	0.8328	78.42	0.6652	0.5621	0.6093	0.707
PV-DBOW	SGD	tanh	[500, 100, 50]	0.7158	0.8321	78.53	0.667	0.5681	0.6136	0.7092
PV-DBOW	SGD	tanh	[100, 50, -]	0.7157	0.8328	78.88	0.6649	0.5613	0.6087	0.7067
PV-DBOW	Adam	logistic	[50, 50, 50]	0.7157	0.8325	78.64	0.6472	0.6087	0.6274	0.7061
PV-DBOW	SGD	tanh	[500, 500, 250]	0.7156	0.8327	78.65	0.6664	0.5651	0.6116	0.7083
PV-DBOW	SGD	tanh	[500, 250, 250]	0.7156	0.8329	78.52	0.6681	0.5666	0.6132	0.7095
PV-DBOW	SGD	tanh	[500, -, -]	0.7156	0.8328	78.76	0.6676	0.5591	0.6085	0.7076
PV-DBOW	SGD	tanh	[500, 100, 100]	0.7154	0.8329	78.52	0.6697	0.5628	0.6116	0.7095
PV-DBOW	SGD	tanh	[250, 50, 50]	0.7154	0.8329	78.78	0.6611	0.5651	0.6093	0.7055
PV-DBOW	SGD	tanh	[100, -, -]	0.7154	0.8324	78.62	0.6625	0.5523	0.6024	0.7037
PV-DBOW	SGD	tanh	[50, 50, -]	0.7154	0.8325	78.58	0.6658	0.5666	0.6122	0.7083
PV-DBOW	Adam	tanh	[500, -, -]	0.7152	0.8335	78.54	0.685	0.468	0.5561	0.6963
PV-DBOW	Adam	logistic	[100, 100, 100]	0.7152	0.8327	78.52	0.6649	0.5538	0.6043	0.7052
PV-DBOW	SGD	tanh	[500, 50, -]	0.715	0.8329	78.6	0.6667	0.5673	0.613	0.7089
PV-DBOW	SGD	tanh	[500, 250, -]	0.7148	0.8325	78.69	0.6664	0.5636	0.6107	0.708
PV-DBOW	SGD	tanh	[500, 250, 100]	0.7147	0.8324	78.41	0.6646	0.5621	0.6091	0.7067
PV-DBOW	SGD	tanh	[250, 100, 100]	0.7147	0.8318	78.47	0.664	0.5636	0.6097	0.7067
PV-DBOW	SGD	logistic	[50, -, -]	0.7147	0.8328	78.62	0.6673	0.5598	0.6088	0.7076
PV-DBOW	Adam	logistic	[100, -, -]	0.7147	0.8327	78.63	0.6686	0.5312	0.592	0.7024
PV-DBOW	SGD	relu	[50, -, -]	0.7145	0.8328	78.38	0.6611	0.5636	0.6084	0.7052
PV-DBOW	Adam	logistic	[50, 50, -]	0.7144	0.8325	78.38	0.6676	0.544	0.5995	0.7046
PV-DBOW	SGD	tanh	[500, 50, 50]	0.7143	0.8322	78.5	0.669	0.5643	0.6122	0.7095
PV-DBOW	SGD	tanh	[500, 500, 100]	0.7142	0.8315	78.38	0.6681	0.5651	0.6123	0.7092
PV-DBOW	Adam	relu	[500, 100, -]	0.714	0.8281	79.44	0.6341	0.5816	0.6068	0.6936
PV-DBOW	Adam	logistic	[500, 500, 250]	0.714	0.832	78.36	0.6703	0.5613	0.611	0.7095
PV-DBOW	SGD	tanh	[100, 100, 50]	0.7139	0.8316	78.34	0.6673	0.5673	0.6133	0.7092
PV-DBOW	Adam	logistic	[500, 250, -]	0.7138	0.8314	78.68	0.6785	0.5192	0.5882	0.7046
PV-DBOW	Adam	logistic	[250, 250, 100]	0.7138	0.8319	78.73	0.6524	0.6072	0.629	0.7089
PV-DBOW	Adam	logistic	[500, 100, 100]	0.7133	0.8315	78.77	0.6623	0.5711	0.6133	0.7073
PV-DBOW	Adam	tanh	[50, -, -]	0.7131	0.8317	78.16	0.6599	0.5606	0.6062	0.704
PV-DBOW	SGD	relu	[500, 50, -]	0.7128	0.8242	79.71	0.618	0.5989	0.6083	0.6865
PV-DBOW	Adam	logistic	[500, 500, 50]	0.7128	0.831	78.52	0.655	0.6072	0.6302	0.7104
PV-DBOW	Adam	logistic	[250, 250, 50]	0.7125	0.8311	78.58	0.6591	0.5892	0.6222	0.7092
PV-DBOW	Adam	logistic	[500, 50, 50]	0.7123	0.8328	78.68	0.6357	0.6343	0.635	0.7037
PV-DBOW	Adam	logistic	[250, 50, 50]	0.7122	0.8317	78.76	0.6722	0.5139	0.5825	0.7006
PV-DBOW	Adam	logistic	[500, 500, -]	0.7117	0.8315	78.78	0.6548	0.608	0.6305	0.7104
PV-DBOW	Adam	logistic	[500, 250, 50]	0.7114	0.8301	78.31	0.666	0.5222	0.5854	0.6994
PV-DBOW	Adam	logistic	[250, 50, -]	0.7113	0.8312	78.68	0.6515	0.6035	0.6266	0.7076
PV-DBOW	Adam	logistic	[500, 500, 500]	0.711	0.8313	78.21	0.6691	0.5568	0.6078	0.708
PV-DBOW	Adam	logistic	[500, 100, -]	0.711	0.8314	78.68	0.6635	0.5711	0.6138	0.708
PV-DBOW	Adam	logistic	[250, 100, -]	0.711	0.8304	78.53	0.6648	0.5403	0.5961	0.7024
PV-DBOW	Adam	logistic	[500, 100, 50]	0.7109	0.8311	78.61	0.6899	0.4838	0.5688	0.7018
PV-DBOW	Adam	logistic	[250, 100, 50]	0.7108	0.8309	78.67	0.6617	0.5711	0.6131	0.707
PV-DBOW	Adam	logistic	[500, 250, 250]	0.7106	0.8304	78.17	0.6562	0.5801	0.6158	0.7058
PV-DBOW	Adam	logistic	[250, 250, 250]	0.7103	0.8298	78.17	0.6676	0.5275	0.5893	0.7012
PV-DBOW	Adam	logistic	[500, 250, 100]	0.71	0.8307	78.6	0.6658	0.5591	0.6078	0.7067
PV-DBOW	Adam	logistic	[500, 50, -]	0.7093	0.8296	78.19	0.6728	0.5199	0.5866	0.7021
PV-DBOW	Adam	logistic	[250, 100, 100]	0.7093	0.8297	78.31	0.655	0.6042	0.6286	0.7098
PV-DBOW	Adam	logistic	[500, 500, 100]	0.7088	0.8305	78.39	0.6654	0.5478	0.6009	0.7043
PV-DBOW	Adam	logistic	[100, 50, 50]	0.7083	0.83	78.22	0.6437	0.6253	0.6344	0.707
PV-DBOW	Adam	relu	[250, 100, 100]	0.7015	0.8172	77.38	0.5863	0.6494	0.6162	0.6713
PV-DBOW	SGD	relu	[500, 500, -]	0.7006	0.8179	78.32	0.6204	0.6027	0.6115	0.6887
PV-DBOW	SGD	relu	[500, 250, 250]	0.7	0.8199	77.32	0.6109	0.6012	0.606	0.6823
PV-DBOW	SGD	relu	[500, 100, -]	0.699	0.8198	78.02	0.6145	0.5937	0.6039	0.6835
PV-DBOW	SGD	relu	[250, 250, 50]	0.6988	0.8125	77.23	0.6056	0.5696	0.587	0.6743
PV-DBOW	SGD	relu	[500, 250, 100]	0.6977	0.82	76.84	0.6097	0.5854	0.5973	0.6792
PV-DBOW	SGD	relu	[250, 250, 250]	0.6976	0.8139	77.73	0.6029	0.5862	0.5944	0.6749
PV-DBOW	SGD	relu	[250, 250, -]	0.6974	0.8184	76.81	0.6016	0.5771	0.5891	0.6728
PV-DBOW	Adam	relu	[500, -, -]	0.6973	0.8177	76.76	0.6268	0.5839	0.6046	0.6896
PV-DBOW	Adam	relu	[500, 50, 50]	0.6946	0.8204	77.34	0.6198	0.6035	0.6115	0.6884
PV-DBOW	SGD	relu	[500, 250, -]	0.6944	0.8152	76.18	0.613	0.5816	0.5969	0.6807
PV-DBOW	SGD	relu	[500, 500, 250]	0.6941	0.8162	77.64	0.6005	0.5711	0.5854	0.6713
PV-DBOW	SGD	relu	[250, 100, -]	0.6939	0.8152	76.73	0.59	0.5922	0.5911	0.667
PV-DBOW	Adam	relu	[250, 100, -]	0.6938	0.8163	76.97	0.6092	0.5666	0.5871	0.6761
PV-DBOW	SGD	relu	[250, 50, -]	0.6933	0.8117	78.16	0.5957	0.5877	0.5917	0.6703
PV-DBOW	Adam	relu	[250, -, -]	0.6932	0.8148	76.87	0.6046	0.5741	0.589	0.6743
PV-DBOW	Adam	relu	[500, 500, -]	0.6927	0.8124	76.81	0.5747	0.6599	0.6144	0.6633
PV-DBOW	Adam	relu	[500, 500, 500]	0.6924	0.8171	77.13	0.6233	0.5839	0.603	0.6875
PV-DBOW	Adam	relu	[100, 100, -]	0.6917	0.8121	76.6	0.6	0.5688	0.584	0.6706
PV-DBOW	Adam	relu	[500, 500, 250]	0.6908	0.8185	76.13	0.6068	0.6561	0.6305	0.6875
PV-DBOW	Adam	relu	[100, 100, 100]	0.6908	0.8105	76.42	0.5951	0.5463	0.5696	0.6645

Experiments using (q, c, avg_com_q) inputs – All results (MAP>0.6).

Category	Solver	Activation	Hidden Layer	MAP	AvgRec	MRR	P	R	F_1	Acc
PV-DBOW	Adam	relu	[250, 250, 50]	0.6902	0.8047	76.05	0.6003	0.5538	0.5761	0.6688
PV-DBOW	SGD	relu	[500, 50, 50]	0.689	0.8114	76.18	0.6038	0.5974	0.6006	0.6771
PV-DBOW	Adam	relu	[500, 100, 100]	0.6889	0.8091	75.52	0.6233	0.5403	0.5788	0.6804
PV-DBOW	Adam	relu	[500, 50, -]	0.6885	0.8147	76.52	0.6255	0.5944	0.6096	0.6905
PV-DBOW	SGD	relu	[250, 250, 100]	0.6883	0.8116	74.95	0.6159	0.5756	0.5951	0.6817
PV-DBOW	SGD	relu	[250, 50, 50]	0.688	0.807	76.93	0.5986	0.5688	0.5833	0.6697
PV-DBOW	Adam	relu	[500, 250, 100]	0.6879	0.8109	76.69	0.608	0.5229	0.5623	0.6691
PV-DBOW	Adam	logistic	[100, 50, -]	0.6877	0.8134	75.84	0.622	0.5275	0.5708	0.6777
PV-DBOW	SGD	relu	[100, 100, -]	0.687	0.8113	77.42	0.5821	0.5764	0.5792	0.6596
PV-DBOW	Adam	relu	[500, 500, 50]	0.6869	0.8108	76.01	0.595	0.6125	0.6036	0.6731
PV-DBOW	Adam	relu	[250, 250, 250]	0.6864	0.8077	75.48	0.6141	0.5688	0.5906	0.6795
PV-DBOW	Adam	relu	[250, 50, 50]	0.6861	0.8103	76.95	0.6116	0.5771	0.5939	0.6792
PV-DBOW	Adam	relu	[250, 250, 100]	0.6859	0.8082	76.68	0.5777	0.6072	0.5921	0.6599
PV-DBOW	Adam	relu	[250, 50, -]	0.6859	0.8124	76.08	0.6308	0.5463	0.5855	0.6856
PV-DBOW	Adam	tanh	[500, 250, 100]	0.6858	0.804	77.83	0.6071	0.5801	0.5933	0.6768
PV-DBOW	SGD	relu	[250, 100, 100]	0.6857	0.8066	75.94	0.5995	0.5824	0.5908	0.6722
PV-DBOW	Adam	relu	[500, 500, 100]	0.6855	0.8143	74.75	0.6569	0.5372	0.5911	0.6979
PV-DBOW	SGD	relu	[500, 100, 50]	0.6841	0.8064	77.55	0.5872	0.5749	0.581	0.663
PV-DBOW	Adam	relu	[250, 250, -]	0.6834	0.802	75.26	0.6039	0.5162	0.5566	0.6657
PV-DBOW	Adam	relu	[50, -, -]	0.683	0.8092	76.38	0.5855	0.5485	0.5664	0.6587
PV-DBOW	SGD	relu	[500, 100, 100]	0.6827	0.8053	75.99	0.5991	0.5824	0.5906	0.6719
PV-DBOW	SGD	relu	[500, 500, 100]	0.6826	0.8076	75.83	0.6103	0.5726	0.5908	0.6777
PV-DBOW	Adam	relu	[250, 100, 50]	0.6825	0.8119	75.69	0.5909	0.5967	0.5938	0.6682
PV-DBOW	SGD	relu	[500, 250, 50]	0.6824	0.8122	76.21	0.6137	0.6132	0.6135	0.6859
PV-DBOW	Adam	relu	[100, -, -]	0.6824	0.8063	75.7	0.5995	0.5824	0.5908	0.6722
PV-DBOW	SGD	relu	[500, 500, 500]	0.6818	0.8054	75.2	0.5922	0.6163	0.604	0.6716
PV-DBOW	Adam	relu	[500, 250, 50]	0.6816	0.8152	75.63	0.6303	0.5132	0.5657	0.6798
PV-DBOW	Adam	relu	[500, 250, -]	0.6802	0.8125	74.16	0.6204	0.5312	0.5724	0.6774
PV-DBOW	Adam	relu	[500, 100, 50]	0.6796	0.8136	74.41	0.6452	0.5282	0.5809	0.6902
PV-DBOW	SGD	relu	[500, 500, 50]	0.6794	0.8061	75.36	0.6008	0.5809	0.5907	0.6728
PV-DBOW	Adam	tanh	[50, 50, -]	0.6792	0.801	75.67	0.5701	0.5688	0.5695	0.6505
PV-DBOW	SGD	relu	[50, 50, 50]	0.6789	0.8029	76.84	0.5881	0.5877	0.5879	0.6651
PV-DBOW	Adam	tanh	[100, -, -]	0.678	0.8026	74.38	0.5924	0.5741	0.5831	0.6664
PV-DBOW	SGD	relu	[250, 100, 50]	0.6767	0.8005	74.68	0.5882	0.5568	0.5721	0.6615
PV-DBOW	Adam	relu	[100, 100, 50]	0.6767	0.7996	74.64	0.5998	0.4929	0.5411	0.6602
PV-DBOW	Adam	tanh	[500, 500, 50]	0.6748	0.799	75.93	0.5947	0.5929	0.5938	0.6703
PV-DBOW	Adam	tanh	[500, 500, 100]	0.673	0.7966	73.96	0.5973	0.5749	0.5859	0.6697
PV-DBOW	Adam	tanh	[500, 250, 250]	0.6729	0.794	73.76	0.6064	0.5959	0.6011	0.6786
PV-DBOW	SGD	relu	[50, 50, -]	0.671	0.7981	75.27	0.584	0.5673	0.5756	0.6599
PV-DBOW	SGD	relu	[100, 50, -]	0.6708	0.7932	75.14	0.5707	0.5651	0.5679	0.6505
PV-DBOW	Adam	tanh	[250, 100, 50]	0.6704	0.7912	74.4	0.599	0.5372	0.5664	0.6657
PV-DBOW	Adam	relu	[100, 50, -]	0.6697	0.7927	75.04	0.56	0.541	0.5503	0.6407
PV-DBOW	SGD	relu	[100, 50, 50]	0.6696	0.797	74.92	0.5833	0.553	0.5678	0.6578
PV-DBOW	Adam	tanh	[500, 250, 50]	0.6691	0.7966	74.67	0.6011	0.5862	0.5935	0.6737
PV-DBOW	Adam	tanh	[500, 100, 100]	0.6689	0.7968	75.45	0.5827	0.5621	0.5722	0.6584
PV-DBOW	Adam	tanh	[250, 250, -]	0.6673	0.796	74.55	0.6018	0.5673	0.584	0.6716
PV-DBOW	SGD	relu	[100, 100, 100]	0.6661	0.7933	74.06	0.5867	0.5756	0.5811	0.6627
PV-DBOW	Adam	tanh	[500, 250, -]	0.6657	0.7898	76.67	0.5843	0.5425	0.5626	0.6572
PV-DBOW	Adam	tanh	[100, 100, 100]	0.6656	0.7921	74.25	0.5873	0.5719	0.5795	0.6627
PV-DBOW	Adam	relu	[50, 50, 50]	0.6655	0.7913	73.14	0.5826	0.5809	0.5818	0.6606
PV-DBOW	Adam	relu	[50, 50, -]	0.665	0.7927	73.82	0.5687	0.5229	0.5449	0.645
PV-DBOW	Adam	tanh	[250, 100, -]	0.6641	0.7907	73.35	0.5932	0.541	0.5659	0.6627
PV-DBOW	SGD	relu	[100, 100, 50]	0.6635	0.7998	73.89	0.5994	0.5809	0.59	0.6719
PV-DBOW	Adam	tanh	[250, 250, 250]	0.6633	0.7923	74.53	0.5917	0.5779	0.5847	0.6664
PV-DBOW	Adam	relu	[100, 50, 50]	0.6615	0.7899	70.95	0.5711	0.6072	0.5886	0.655
PV-DBOW	Adam	tanh	[500, 500, 250]	0.6614	0.7936	74.14	0.6085	0.5719	0.5896	0.6765
PV-DBOW	Adam	tanh	[500, 100, -]	0.6611	0.783	73.24	0.5685	0.5591	0.5637	0.6483
PV-DBOW	Adam	tanh	[100, 100, -]	0.6609	0.7917	74.31	0.5969	0.5214	0.5566	0.6624
PV-DBOW	Adam	tanh	[250, 250, 50]	0.6607	0.7914	73.87	0.586	0.5335	0.5585	0.6572
PV-DBOW	Adam	tanh	[500, 50, -]	0.6588	0.7872	73.37	0.5839	0.5523	0.5677	0.6581
PV-DBOW	Adam	tanh	[250, 250, 100]	0.6588	0.7905	73.31	0.5886	0.5448	0.5658	0.6602
PV-DBOW	Adam	tanh	[500, 100, 50]	0.6586	0.7934	74.55	0.5929	0.5786	0.5857	0.6673
PV-DBOW	Adam	tanh	[500, 500, 500]	0.6576	0.7848	73.9	0.6056	0.5719	0.5882	0.6746
PV-DBOW	Adam	tanh	[500, 500, -]	0.6567	0.7841	72.29	0.575	0.5681	0.5715	0.6538
PV-DBOW	Adam	tanh	[250, 100, 100]	0.6567	0.7816	72.83	0.556	0.5673	0.5616	0.6401
PV-DBOW	Adam	tanh	[250, 50, 50]	0.6551	0.7845	73.46	0.5917	0.5606	0.5757	0.6642
PV-DBOW	Adam	tanh	[100, 100, 50]	0.6537	0.7766	72.16	0.5758	0.5546	0.565	0.6529
PV-DBOW	Adam	tanh	[100, 50, -]	0.6537	0.7844	72.16	0.5842	0.5561	0.5698	0.6587
PV-DBOW	Adam	tanh	[250, 50, -]	0.6497	0.7818	73.01	0.5789	0.541	0.5593	0.6535
PV-DBOW	Adam	tanh	[500, 50, 50]	0.6494	0.7765	72.93	0.5772	0.5342	0.5549	0.6517
PV-DBOW	Adam	tanh	[100, 50, 50]	0.6445	0.7727	71.17	0.5549	0.5666	0.5607	0.6391
PV-DBOW	Adam	tanh	[50, 50, 50]	0.6403	0.7722	71.21	0.576	0.5561	0.5658	0.6532

Experiments using (q, c, avg_com_q) inputs – All results (MAP>0.6).

Appendix D

Further experiments with Syntactic & Metadata features

Category	Solver	Activation	Hidden Layer	MAP	AvgRec	MRR	P	R	F_1	Acc
PV-DBOW	SGD	tanh	[250, 250, 50]	0.7774	0.882	85.58	0.7081	0.6351	0.6696	0.7453
PV-DBOW	SGD	relu	[250, 100, 50]	0.7743	0.8796	84.81	0.7057	0.626	0.6635	0.7419
PV-DBOW	SGD	logistic	[500, 100, 100]	0.7726	0.8787	85.51	0.7149	0.6358	0.673	0.7489
PV-DBOW	SGD	logistic	[100, 100, 50]	0.7726	0.8798	85.1	0.7122	0.6313	0.6693	0.7465
PV-DBOW	SGD	logistic	[500, 500, 100]	0.7723	0.8787	85.51	0.709	0.6305	0.6675	0.7446
PV-DBOW	SGD	tanh	[250, 100, -]	0.7722	0.8801	84.81	0.7046	0.6336	0.6672	0.7431
PV-DBOW	SGD	relu	[250, 250, 250]	0.7721	0.8788	84.88	0.7071	0.6268	0.6645	0.7428
PV-DBOW	SGD	relu	[250, 50, -]	0.7721	0.8785	84.7	0.7117	0.6298	0.6683	0.7459
PV-DBOW	SGD	tanh	[250, 250, -]	0.7721	0.8787	84.7	0.7066	0.6305	0.6664	0.7434
PV-DBOW	SGD	tanh	[50, 50, -]	0.7718	0.8793	85.37	0.7096	0.6343	0.6698	0.7459
PV-DBOW	SGD	relu	[250, 50, 50]	0.7716	0.8797	84.79	0.7065	0.6268	0.6643	0.7425
PV-DBOW	SGD	tanh	[500, 50, -]	0.7716	0.8792	84.98	0.7149	0.6396	0.6751	0.7498
PV-DBOW	SGD	tanh	[500, 250, 50]	0.7715	0.8795	84.93	0.7134	0.6351	0.672	0.748
PV-DBOW	SGD	tanh	[500, -, -]	0.7715	0.8786	84.83	0.7013	0.6305	0.664	0.7407
PV-DBOW	SGD	tanh	[500, 100, 50]	0.7712	0.8796	84.94	0.7125	0.6396	0.6741	0.7486
PV-DBOW	SGD	tanh	[250, 50, -]	0.7711	0.8776	85.36	0.7083	0.6358	0.6701	0.7456
PV-DBOW	SGD	tanh	[250, 100, 50]	0.771	0.8785	84.85	0.7124	0.6411	0.6749	0.7489
PV-DBOW	SGD	relu	[250, 250, 100]	0.7709	0.8779	84.72	0.7032	0.6185	0.6581	0.7388
PV-DBOW	SGD	tanh	[500, 500, 250]	0.7709	0.8792	85.06	0.7024	0.6305	0.6646	0.7413
PV-DBOW	SGD	tanh	[250, 250, 100]	0.7709	0.8789	84.69	0.7081	0.626	0.6645	0.7431

TABLE 11: Experiments using $(q, c, avg\_com_q, ft_{(q,c)})$ inputs – All results.

Category	**Solver**	**Activation**	**Hidden Layer**	**MAP**	**AvgRec**	**MRR**	**P**	**R**	$\mathbf{F_1}$	**Acc**
PV-DBOW	SGD	tanh	[100, -, -]	0.7707	0.8785	84.9	0.7192	0.6321	0.6728	0.7502
PV-DBOW	SGD	tanh	[250, 250, 250]	0.7705	0.8791	84.69	0.7023	0.6336	0.6661	0.7419
PV-DBOW	SGD	tanh	[500, 250, 250]	0.7704	0.8799	85.3	0.7089	0.6396	0.6725	0.7468
PV-DBOW	SGD	tanh	[500, 500, 500]	0.7703	0.8785	84.91	0.7069	0.6388	0.6711	0.7456
PV-DBOW	SGD	tanh	[250, 100, 100]	0.7703	0.8786	84.79	0.7046	0.6283	0.6643	0.7419
PV-DBOW	SGD	logistic	[500, 500, 500]	0.7702	0.8771	85.03	0.7088	0.6283	0.6661	0.744
PV-DBOW	SGD	tanh	[50, 50, 50]	0.77	0.8779	84.92	0.7084	0.6343	0.6693	0.7453
PV-DBOW	SGD	logistic	[50, 50, 50]	0.77	0.8775	85.18	0.7109	0.629	0.6675	0.7453
PV-DBOW	SGD	logistic	[500, 250, 50]	0.7698	0.8771	84.87	0.7128	0.6275	0.6675	0.7459
PV-DBOW	SGD	logistic	[250, 250, 50]	0.7698	0.8773	84.98	0.7079	0.629	0.6661	0.7437
PV-DBOW	SGD	logistic	[100, 50, -]	0.7697	0.8779	84.75	0.713	0.6336	0.6709	0.7474
PV-DBOW	SGD	logistic	[500, 250, 250]	0.7696	0.8769	84.95	0.7047	0.623	0.6613	0.7407
PV-DBOW	SGD	relu	[250, 100, -]	0.7695	0.876	84.56	0.7065	0.6178	0.6592	0.7404
PV-DBOW	SGD	tanh	[500, 100, -]	0.7695	0.8781	84.34	0.7065	0.6321	0.6672	0.7437
PV-DBOW	SGD	logistic	[500, 500, -]	0.7695	0.8765	85.1	0.7043	0.6238	0.6616	0.7407
PV-DBOW	SGD	tanh	[500, 500, -]	0.7693	0.8794	84.63	0.7051	0.6351	0.6683	0.7437
PV-DBOW	SGD	tanh	[250, 50, 50]	0.7692	0.8776	84.9	0.705	0.6366	0.669	0.744
PV-DBOW	SGD	tanh	[100, 50, -]	0.7692	0.8786	84.98	0.7058	0.6283	0.6648	0.7425
PV-DBOW	SGD	relu	[250, 250, -]	0.769	0.8773	84.98	0.7114	0.6268	0.6664	0.745
PV-DBOW	SGD	relu	[500, 500, 500]	0.7689	0.8766	83.14	0.7003	0.6313	0.664	0.7404
PV-DBOW	SGD	tanh	[500, 100, 100]	0.7689	0.8795	84.98	0.7096	0.6343	0.6698	0.7459
PV-DBOW	SGD	logistic	[100, 50, 50]	0.7689	0.8767	84.93	0.7126	0.6268	0.6669	0.7456
PV-DBOW	SGD	tanh	[50, -, -]	0.7688	0.8764	84.46	0.7115	0.6366	0.672	0.7474
PV-DBOW	SGD	logistic	[250, 50, 50]	0.7688	0.8763	84.85	0.7099	0.626	0.6653	0.744
PV-DBOW	SGD	tanh	[250, -, -]	0.7687	0.8782	84.94	0.7032	0.6275	0.6632	0.741
PV-DBOW	SGD	tanh	[100, 100, 100]	0.7685	0.8765	84.99	0.7126	0.6268	0.6669	0.7456
PV-DBOW	SGD	logistic	[250, 100, -]	0.7685	0.8762	85.08	0.7068	0.6223	0.6619	0.7416
PV-DBOW	SGD	logistic	[500, 100, -]	0.7684	0.8767	84.98	0.7055	0.6238	0.6621	0.7413
PV-DBOW	SGD	tanh	[100, 100, -]	0.768	0.8775	84.99	0.7063	0.6298	0.6659	0.7431
PV-DBOW	SGD	logistic	[500, 500, 250]	0.768	0.8762	84.95	0.7057	0.626	0.6635	0.7419
PV-DBOW	SGD	logistic	[500, 250, 100]	0.768	0.876	84.87	0.704	0.6245	0.6619	0.7407
PV-DBOW	SGD	logistic	[50, 50, -]	0.7677	0.8744	84.94	0.7041	0.623	0.6611	0.7404
PV-DBOW	SGD	relu	[100, 50, 50]	0.7676	0.8752	84.37	0.7106	0.6373	0.672	0.7471
PV-DBOW	SGD	logistic	[500, 50, -]	0.7676	0.8751	84.82	0.7045	0.6208	0.66	0.7401
PV-DBOW	SGD	logistic	[250, 100, 50]	0.7676	0.8762	84.67	0.7093	0.6298	0.6672	0.7446
PV-DBOW	SGD	tanh	[500, 50, 50]	0.7675	0.877	85.12	0.7054	0.6305	0.6659	0.7428
PV-DBOW	SGD	logistic	[100, 100, -]	0.7675	0.8759	84.68	0.7136	0.626	0.6669	0.7459
PV-DBOW	SGD	relu	[500, -, -]	0.7674	0.8771	84.19	0.7159	0.6238	0.6667	0.7465
PV-DBOW	SGD	tanh	[100, 100, 50]	0.7674	0.8772	84.6	0.7099	0.6223	0.6632	0.7431
PV-DBOW	SGD	relu	[250, 250, 50]	0.7673	0.877	84.26	0.7044	0.6223	0.6608	0.7404
PV-DBOW	SGD	logistic	[500, 50, 50]	0.7673	0.8744	85.07	0.7004	0.614	0.6544	0.7364

Experiments using $(q, c, avg\_com_q, ft_{(q,c)})$ inputs – All results.

Category	Solver	Activation	Hidden Layer	MAP	AvgRec	MRR	P	R	F_1	Acc
PV-DBOW	SGD	logistic	[100, 100, 100]	0.7673	0.8762	84.49	0.7098	0.6275	0.6661	0.7443
PV-DBOW	SGD	tanh	[500, 250, 100]	0.7672	0.8775	84.76	0.7065	0.6321	0.6672	0.7437
PV-DBOW	SGD	logistic	[500, 500, 50]	0.767	0.876	84.64	0.7069	0.626	0.664	0.7425
PV-DBOW	SGD	logistic	[250, 100, 100]	0.767	0.8755	84.86	0.7075	0.626	0.6643	0.7428
PV-DBOW	SGD	logistic	[500, 250, -]	0.7669	0.8749	84.93	0.7013	0.6253	0.6611	0.7394
PV-DBOW	SGD	logistic	[250, 50, -]	0.7669	0.875	84.75	0.7054	0.6253	0.6629	0.7416
PV-DBOW	SGD	relu	[500, 250, 250]	0.7668	0.8764	84.17	0.714	0.6275	0.668	0.7465
PV-DBOW	SGD	tanh	[500, 250, -]	0.7668	0.8779	84.68	0.705	0.6366	0.669	0.744
PV-DBOW	SGD	logistic	[500, 100, 50]	0.7667	0.8751	84.89	0.7047	0.623	0.6613	0.7407
PV-DBOW	SGD	tanh	[500, 500, 50]	0.7666	0.8783	84.14	0.712	0.6343	0.6709	0.7471
PV-DBOW	SGD	relu	[50, 50, 50]	0.7664	0.8743	84.63	0.7042	0.6215	0.6603	0.7401
PV-DBOW	SGD	tanh	[100, 50, 50]	0.7664	0.8777	84.46	0.7128	0.6313	0.6696	0.7468
PV-DBOW	SGD	logistic	[500, -, -]	0.7658	0.8734	84.45	0.704	0.6193	0.6589	0.7394
PV-DBOW	SGD	logistic	[250, 250, 250]	0.7657	0.875	84.57	0.7056	0.6223	0.6613	0.741
PV-DBOW	SGD	logistic	[100, -, -]	0.7657	0.8753	84.58	0.7095	0.623	0.6635	0.7431
PV-DBOW	SGD	relu	[100, 100, -]	0.7656	0.8763	84.67	0.7048	0.6163	0.6576	0.7391
PV-DBOW	SGD	relu	[100, 50, -]	0.7656	0.8744	84.81	0.7071	0.623	0.6624	0.7419
PV-DBOW	SGD	logistic	[250, 250, -]	0.7655	0.8748	84.8	0.7063	0.626	0.6637	0.7422
PV-DBOW	SGD	relu	[500, 100, 100]	0.7654	0.8768	83.85	0.7098	0.6313	0.6683	0.7453
PV-DBOW	SGD	logistic	[50, -, -]	0.7652	0.874	84.72	0.707	0.6193	0.6602	0.741
PV-DBOW	SGD	relu	[500, 500, -]	0.7649	0.8762	84.1	0.7138	0.6305	0.6696	0.7471
PV-DBOW	SGD	relu	[500, 50, -]	0.7649	0.8765	84.12	0.7169	0.6305	0.6709	0.7486
PV-DBOW	SGD	relu	[500, 100, -]	0.7646	0.8759	84.26	0.7145	0.6366	0.6733	0.7489
PV-DBOW	SGD	tanh	[500, 500, 100]	0.7646	0.8771	83.81	0.7053	0.6321	0.6667	0.7431
PV-DBOW	SGD	logistic	[250, 250, 100]	0.7645	0.8739	84.67	0.699	0.6238	0.6592	0.7379
PV-DBOW	SGD	relu	[50, -, -]	0.7643	0.873	84.08	0.7174	0.6245	0.6677	0.7474
PV-DBOW	SGD	relu	[500, 250, -]	0.7642	0.8749	84.02	0.7018	0.6268	0.6622	0.7401
PV-DBOW	SGD	relu	[250, 100, 100]	0.7641	0.8761	84.26	0.7155	0.6283	0.6691	0.7474
PV-DBOW	SGD	relu	[500, 500, 250]	0.7639	0.8761	84.29	0.7092	0.6238	0.6637	0.7431
PV-DBOW	SGD	relu	[500, 500, 100]	0.7639	0.8754	83.89	0.7142	0.626	0.6672	0.7462
PV-DBOW	SGD	relu	[50, 50, -]	0.7638	0.8744	84.46	0.7139	0.629	0.6688	0.7468
PV-DBOW	SGD	logistic	[250, -, -]	0.7637	0.8729	84.33	0.7021	0.617	0.6568	0.7379
PV-DBOW	SGD	relu	[100, 100, 50]	0.7636	0.8753	83.91	0.7087	0.6223	0.6627	0.7425
PV-DBOW	SGD	relu	[500, 250, 50]	0.7633	0.8757	84.27	0.7109	0.6253	0.6653	0.7443
PV-DBOW	SGD	relu	[500, 500, 50]	0.7631	0.8756	83.85	0.7159	0.6313	0.6709	0.7483
PV-DBOW	SGD	relu	[100, 100, 100]	0.7629	0.8738	83.68	0.7038	0.6185	0.6584	0.7391
PV-DBOW	SGD	relu	[500, 250, 100]	0.7628	0.8749	83.82	0.7109	0.6328	0.6696	0.7462
PV-DBOW	SGD	relu	[500, 50, 50]	0.7625	0.8737	83.85	0.7113	0.6193	0.6621	0.7431
PV-DBOW	SGD	relu	[500, 100, 50]	0.7624	0.8721	83.6	0.7067	0.62	0.6605	0.741
PV-DBOW	SGD	relu	[250, -, -]	0.7616	0.8723	83.69	0.7079	0.611	0.6559	0.7394
PV-DBOW	SGD	relu	[100, -, -]	0.759	0.8703	83.7	0.7116	0.6163	0.6605	0.7425

Experiments using $(q, c, avg\_com_q, ft_{(q,c)})$ inputs – All results.

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