Semantic Encoding of Review Sentences for Memory-Based Recommenders

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DIG Seminar - 2/22/22 (!)

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Introduction (1/3)

Sunday afternoon, you're at home and your partner/roommate/friend is out and texts you to know whether you would like to watch "Split" tonight, a movie you've never heard of.

What would you do?

Introduction (1/3)

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What would you do?

Use a search engine to obtain information about it.

- Have you seen this movie? 🙋

Introduction (2/3): Various levels of interaction **feedback**

- Have you seen this movie? 🙋
- How would you rate this movie? ☝, ✌, $\cdots$, 🖐

Introduction (2/3): Various levels of interaction **feedback**

- Have you seen this movie? 🙋
- How would you rate this movie? ☝️, ✌️, $\cdots$, ✋
- Can you say a word on what you liked or disliked? 🗣️

Introduction (2/3): Various levels of interaction **feedback**

- Have you seen this movie? 🙋
  →**Implicit feedback**
- How would you rate this movie?
  ☝, ✌, $\cdots$, ✋
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Introduction (2/3): Various levels of interaction **feedback**

- Have you seen this movie? 🙋
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- How would you rate this movie?
  ☝, ✌, . . . , 🖐
  →**Explicit feedback**
- Can you say a word on what you liked or disliked? 🗣
  →**Review feedback**

Introduction (3/3): Motivations

- Show **personalized prediction scores** to users of a search engine
- Use **what users expressed** in past reviews to make predictions
- Extract "**rationales**" for predictions

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Datasets (1/2): 2014 **Amazon** Product Reviews

- Narrowed down to the 20-**core movie** subset.

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Item name	Spirited away $\in I$
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- Example:

User id	A10HHM2684NZD2 $\in U$
Item name	Spirited away $\in I$
Date	June 28, 2005
Rating	5/5
Review	This is one of the most well told tales i ' ve ever had the pleasure of experienceing . Essensially it's a story of how this little girl learns how to overcome adversity , at the same time learns how to care for someone . This movie will tug at your heart strings . A masterpiece for all ages to enjoy .

Datasets (2/2): Yelp business Reviews

- Narrowed down to the 20-**core** subset.
- 2M reviews broke down into 20**M sentences**
- Example:

User id	KvLseJGLjDXa4oqJf7KBGA $\in U$
Item name	The Cheescake Factory (Boston) $\in I$
Date	May 12, 2012
Rating	3/5
Review	The portions are RIDICULOUS and the menu gives me vertigo. When I eat off the regular menu I feel like I need to spend the next 24 hours at the gym ... BUT their seasonal pumpkin pecan cheesecake is amazing and, in my heart, I believe it is zero calories.

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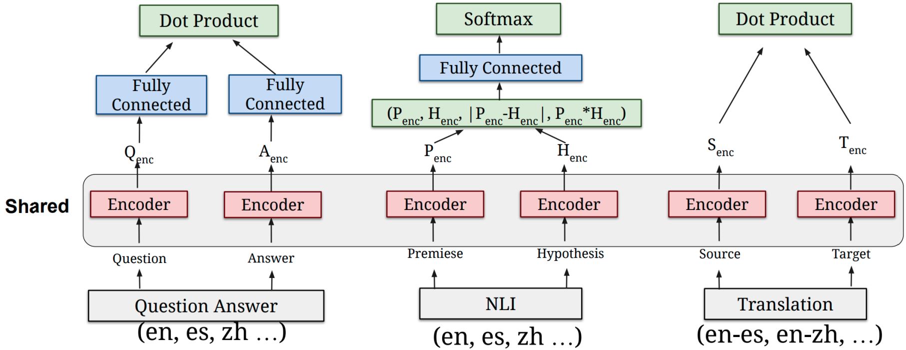
Semantic matching (1/5): **Universal Sentence Encoder** is trained to produce semantic embeddings [3]



Transformer [1] or **CNN** [2] based sentence embedding models provide a shared **encoder** across all tasks.

Pre-trained and available **on-the-shelf**!

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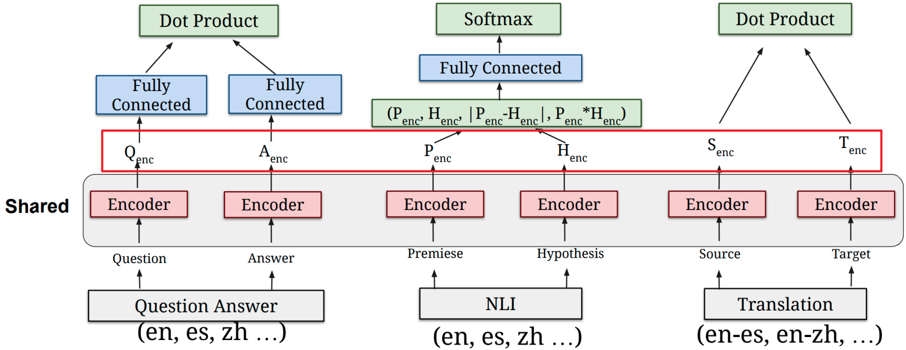
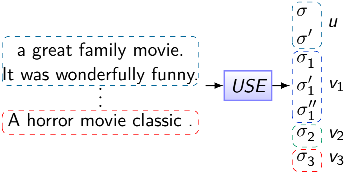


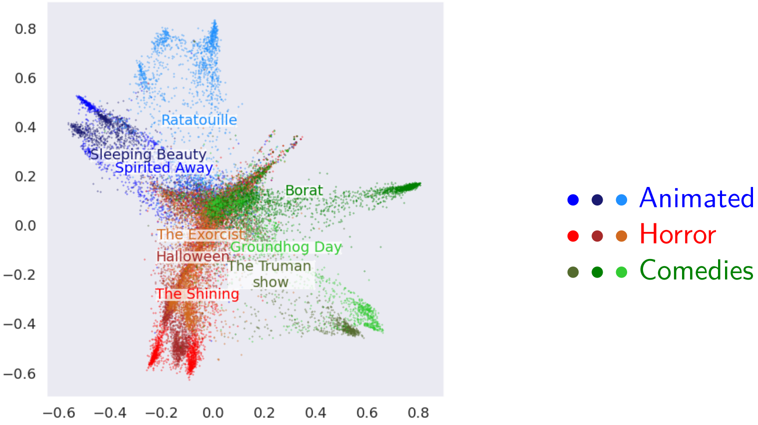
Transformer [1] or **CNN** [2] based sentence embedding models provide a shared **encoder** across all tasks.

Pre-trained and available **on-the-shelf**!

Semantic matching (2/5): Users are represented by their **sentence embeddings**

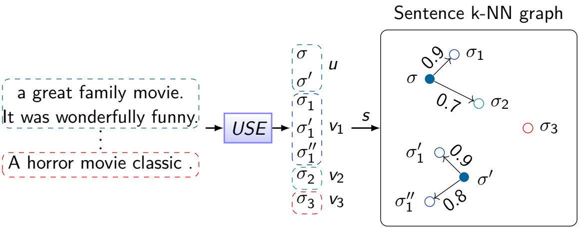


Semantic matching (3/5): Sentences are somehow **clustered** on categories



2D t-SNE projection of sentence embeddings.

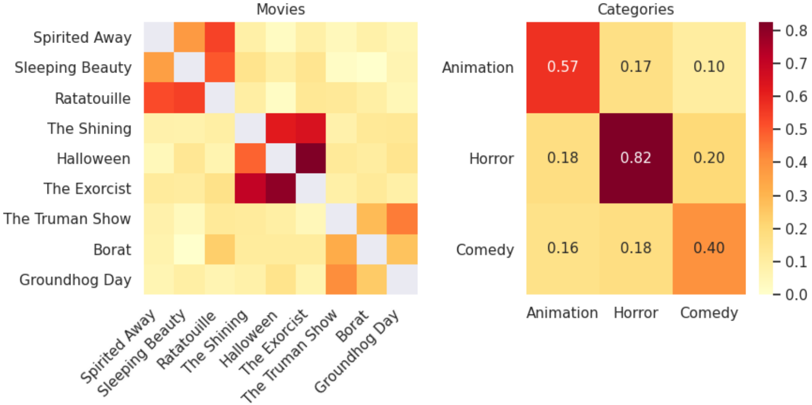
Semantic matching (4/5): We computed the **k-NN directed graph** of the **sentence embeddings**



Semantic match

A pair of sentences connected in the graph: (σ, σ_1) is a match while (σ, σ_3) is not.

Semantic matching (5/5): **Sentence matching** as proxy for close semantics and preferences



Heatmaps of k-NN sentence embedding matches where $k = 10$. Rows and columns respectively represent head and tail vertices.

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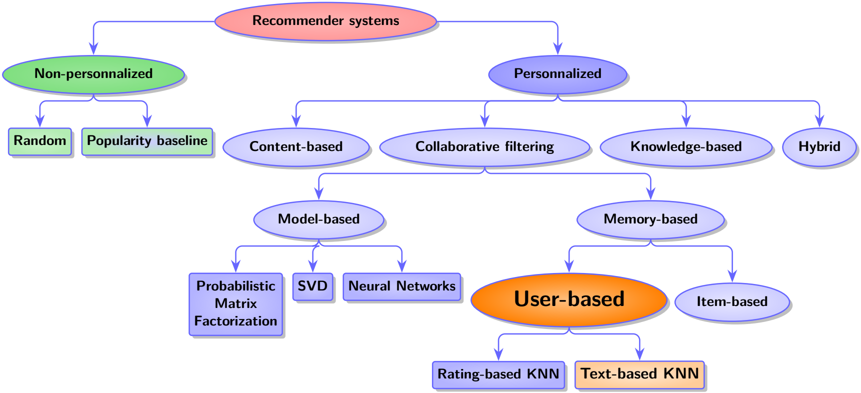
Recommender system (1/3): Hierarchy of systems



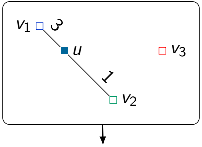
Recommender system (2/3): **Collaborative filtering** makes predictions from **preferences shared by users**.

Moshanin, CC BY-SA 3.0, via Wikimedia Commons

Recommender system (3/3): Memory-based systems are **k-NN regressors** on users

$$\hat{r}_{uj} = \frac{\sum_{v \in N_j^{k'}(u)} w(u,v) \cdot r_{vj}}{\sum_{v \in N_j^{k'}(u)} w(u,v)}$$

User k-NN regressor



$\hat{r}_{uj} = \frac{3}{4} \cdot r_{v_1 j} + \frac{1}{4} \cdot r_{v_2 j}$

r_{vj}: Ground-truth rating of user v on item j.
$N_j^{k'}(u)$: Set of k' nearest neighbor users of user u who have rated item i.
$w(u,v)$: **Weight of v for predicting u's rating.**

Pros:

- Simplicity of implementation and understanding.
- Ease of creating explanations.

Cons:

- Less accurate than SOTA model-based systems.

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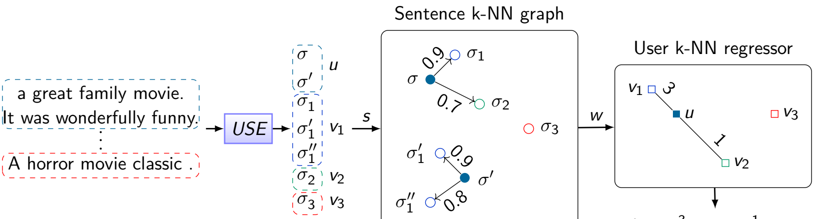
Text-KNN (1/1): We propose a **k-NN regressor** based on **counting semantic matches**



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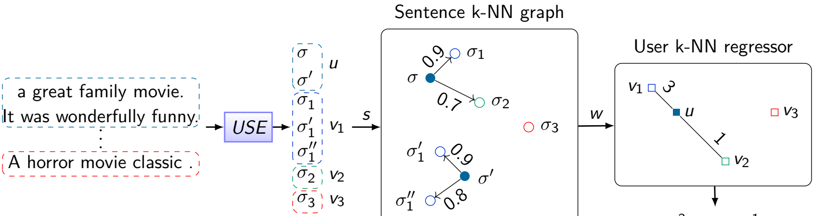

$$\hat{r}_{uj} = \frac{3}{4} \cdot r_{v_1 j} + \frac{1}{4} \cdot r_{v_2 j}$$

3 ways of computing the user weights $w(u, v)$

1. **One-to-One matching**: u and v have expressed similar preferences if v wrote at least one sentence in the semantic neighborhood of at least one sentence written by u.

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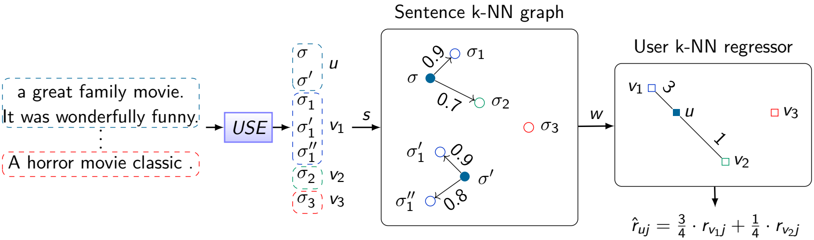

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1. **One-to-One matching**: u and v have expressed similar preferences if v wrote at least one sentence in the semantic neighborhood of at least one sentence written by u.
2. **Many-to-One matching**: $w(u, v)$ counts the occurrence of v's sentences in the neighborhood of u's sentences.

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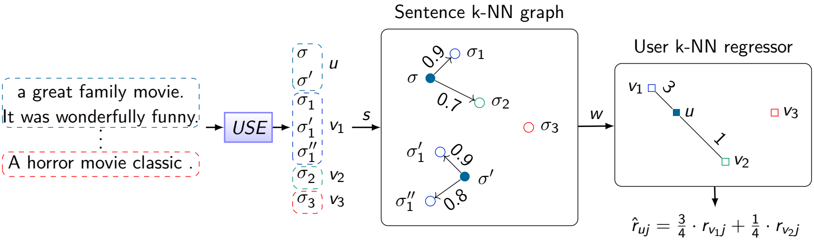

3 ways of computing the user weights $w(u, v)$

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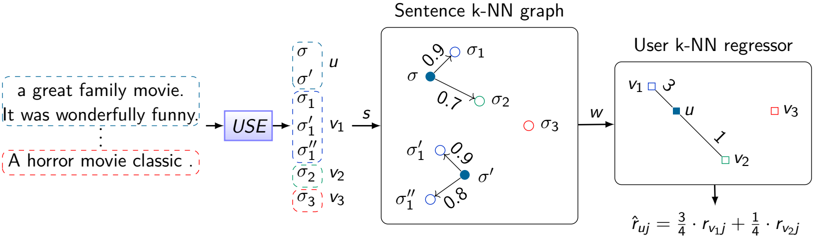
2. **Many-to-One matching**: $w(u, v)$ counts the occurrence of v's sentences in the neighborhood of u's sentences.
3. **Many-to-Many matching**: $w(u, v)$ counts the number of sentence matches when considering all pairs of sentences written by u and v.

Text-KNN (1/1): We propose a **k-NN regressor** based on **counting semantic matches**



Options to compute the sentence weights $s(\sigma_1, \sigma_2)$

1. **Binary count**: $s(\sigma_1, \sigma_2) = 1$ iif (σ_1, σ_2) is a match and 0 otherwise.

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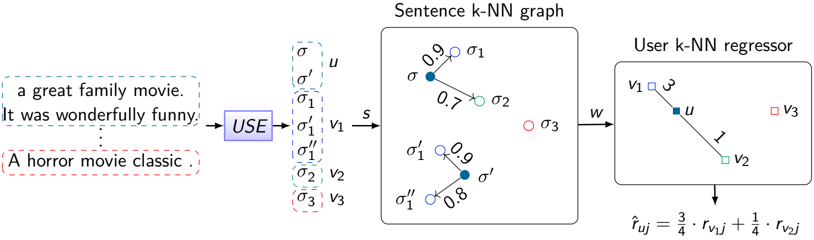

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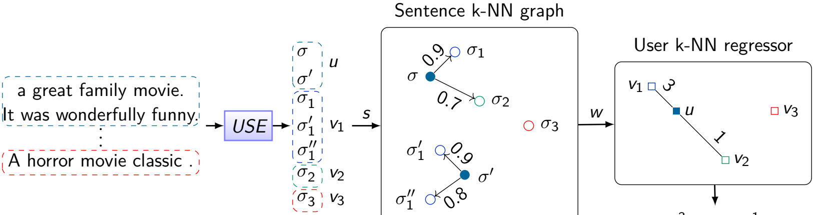

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3. **Polarization**: cosine similarity(“I love DiCaprio”, “I hate DiCaprio”)$= 0.94$. Polarization multiplies by -1 the matches where the pair is made of sentences from opposite-sentiment reviews.

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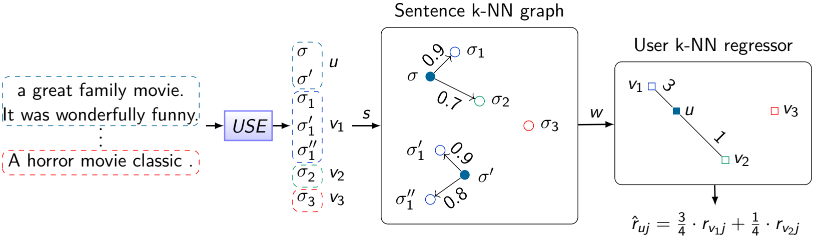

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4. **Per-item graph**: instead of the graph of all sentences, we focused on per-item graphs before aggregating.

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Evaluation (1/2): Existing accuracy **metrics**

<table>
<tr><th>Task</th><th>Rating prediciton</th><th>Item recommendation</th></tr>
<tr><td>Predictive accuracy</td><td>RMSE, MAE, MSE</td><td></td></tr>
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Task	**Rating prediciton**	Item recommendation
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Classification	Precision, Recall, ROC, ROC-AUC	Precision, Recall, ROC, ROC-AUC
Rank correlation	Spearman ρ, Kendall τ, **FCP**	Spearman ρ, Kendall τ, **FCP**
Next-interaction rank		HR@N, nDCG, MR, MRR

Root-**M**ean-**S**quare **E**rror

$$\text{RMSE} = \sqrt{\frac{\sum\limits_{(u,i)\in \text{Test Set}} (\hat{r}_{ui} - r_{ui})^2}{|\text{Test Set}|}}$$

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Rank correlation	Spearman ρ, Kendall τ, **FCP**	
Next-interaction rank		HR@N, nDCG, MR, MRR

Fraction of Concordant Pairs

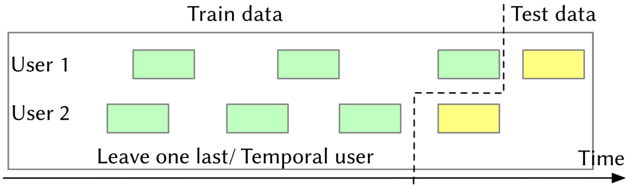
For two items i and j rated by the same user u, i.e. (u, i) and (u, j) in the Test Set, a pair $((r_{ui}, \hat{r}_{ui}), (r_{uj}, \hat{r}_{uj}))$ is:

- Concordant (c) iif $r_{ui} \neq r_{uj}$ and $\operatorname{sgn}(r_{ui} - r_{uj}) = \operatorname{sgn}(\hat{r}_{ui} - \hat{r}_{uj})$,
- Discordant (d) iif $r_{ui} \neq r_{uj}$ and $\operatorname{sgn}(r_{ui} - r_{uj}) \neq \operatorname{sgn}(\hat{r}_{ui} - \hat{r}_{uj})$,
- Ignored if $r_{ui} = r_{uj}$

$\text{FCP} = \frac{n_c}{n_c + n_d}$ ❗ Assumes several test items per user in the test set.

Evaluation (2/2): **T**ime-based **F**raction of **C**oncordant **P**airs

Leave One Last Item strategy splits the set in train/test [4].



For a user u, each pair $\left(\left(r_{ui}, \hat{r}_{ui}\right), \left(r_{uj}, \hat{r}_{uj}\right)\right)$ is made of *a* train item i and *the* test item j.

$\text{TFCP}(u) = \frac{n_c(u)}{n_c(u)+n_d(u)}$ indicates how well the system ranks the test item compared to the train items, according to u.

$\text{TFCP} = \sum_{u \in U} \text{TFCP}(u)$ macro-averages $\text{TFCP}(u)$ on all users.

TFCP generalizes AUC for non-binary variables.

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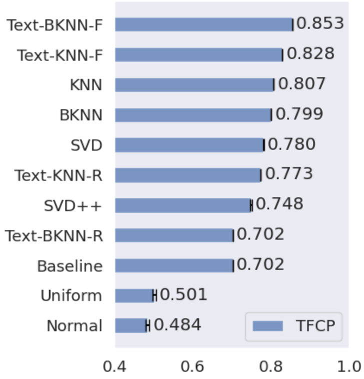
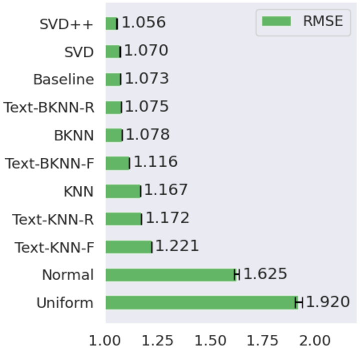
Results (1/3): **Amazon** dataset



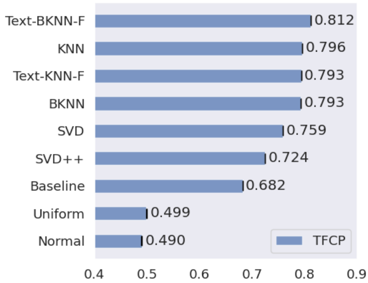


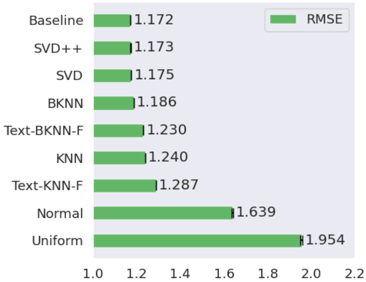
Baseline: $b_{ui} = \mu + b_u + b_i$

KNN: $$\hat{r}_{uj} = \frac{\sum_{v \in N_j^{k'}(u)} w(u,v) \cdot r_{vj}}{\sum_{v \in N_j^{k'}(u)} w(u,v)}$$

BKNN: $$\hat{r}_{uj} = b_{ui} + \frac{\sum_{v \in N_j^{k'}(u)} w(u,v) \cdot (r_{vj} - b_{vi})}{\sum_{v \in N_j^{k'}(u)} w(u,v)}$$

Results (2/3): **Yelp** dataset

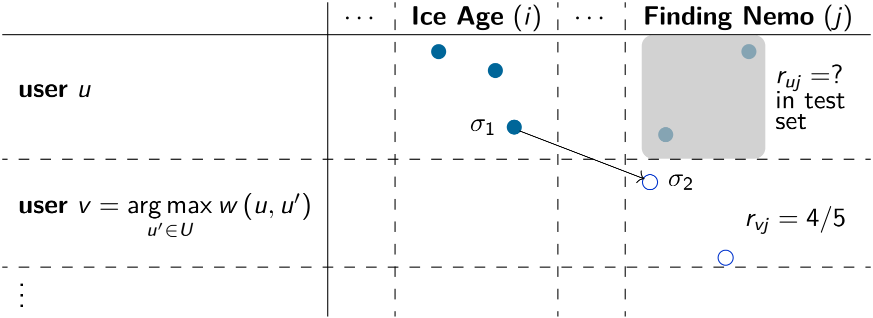




Note: Hyperparameters are not tuned on the Yelp dataset.

Results (3/3): **Scrutability** of recommender systems

Semantic matches could be used for endorsement of recommendations.



Text-KNN predicts that you will rate *Finding Nemo* with $\hat{r}_{uj} \approx r_{vj} = \mathbf{4/5}$ because you expressed "$\boldsymbol{\sigma_1}$" on *Ice Age* and it resembles what the user closest to you expressed when they reviewed *Finding Nemo*: "$\boldsymbol{\sigma_2}$".

Results (3/3): **Scrutability** of recommender systems

Head sentence σ_1 written by u on some item i	Tail sentence σ_2 written by v on u's test item j and matching σ_1
Cemetery Man – This highly entertaining little zombie movie from Italy has all the elements that make it a wonderfully dark horror - comedy in the same vein asEvil Dead 2 : Dead by DawnandAn American Werewolf in London .	**The Horde** – one of the best horror zombie movies of all the times , this movie is equal than 28 days later , in these days European horror movies are the best of the best . . good for Friday at night
Charlie's Angels – I like drew barrymore , she is the best angel out of the three .	**Fever Pitch** – Drew Barrymore , as always , is phenomenal .
Ice Age – While not perfect , it is full of laughs and beautiful computer animation .	**Finding Nemo** – Highlights : Spectacular computer animation ; hilarious , well - developed characters ; original plot .
Monsters, Inc. – Great for parents and kids (or people without kids) .	**Toy Story 3** – Great for kids and adults alike.
Island in the Sky – The Duke[1] does a great job in his role as Dooley - the plane's captain.	**The Alamo** – The Duke turns out one of his best performances , as well as putting together this film .

[1] A nickname for the American actor John Wayne

Contents

Conclusion

- Text-KNN integrates **review feedback** in traditionnal memory-based systems.
- It achieves **competitive results** when compared with baselines and SOTA systems.
- **Evaluation** of recommender systems is an **open-research** topic.
- Work submitted to **KDD'22**.

Future work

- Supervised or unsupervised **pruning** of irrelevant sentences in reviews, e.g. "I like this movie"
- **Better semantic embedding**, suited to recommendation
- Theory on why **ranking-based metrics** evaluate recommenders better than error-based metrics.

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