Modeling Personal Biases in Language Use by Inducing Personalized Word Embeddings

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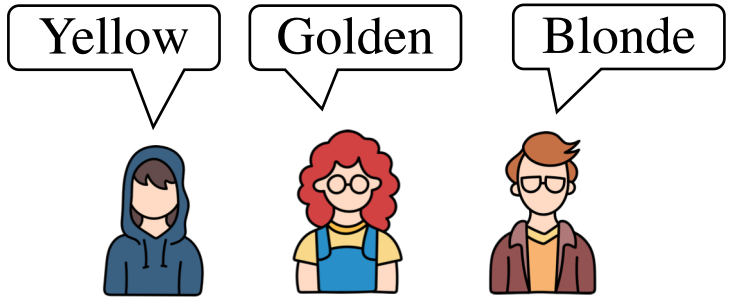
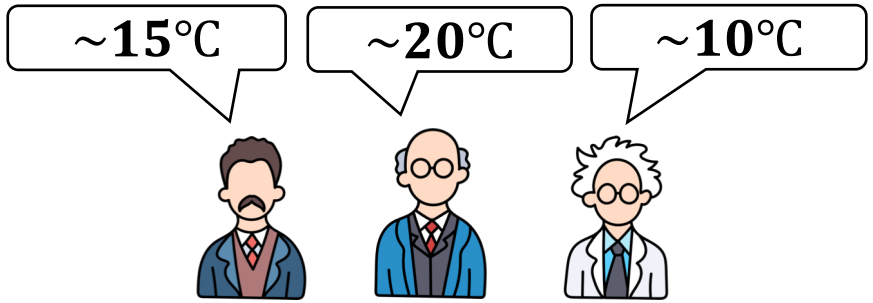
Word meanings vary depending on each person

What color?



How much temperature does the word "Cold" represent?



Personal semantic variations

- 😟 Prevent our smooth communication in our daily life
- 😟 Degrade the ability for computer to process documents

Goal of our research

Understanding **personal semantic variations**

RQ1: Modeling personal sem. var. makes the performance of NLP tasks better?

e.g., **sentiment analysis**

RQ2: What kind of words have large personal sem. var.?

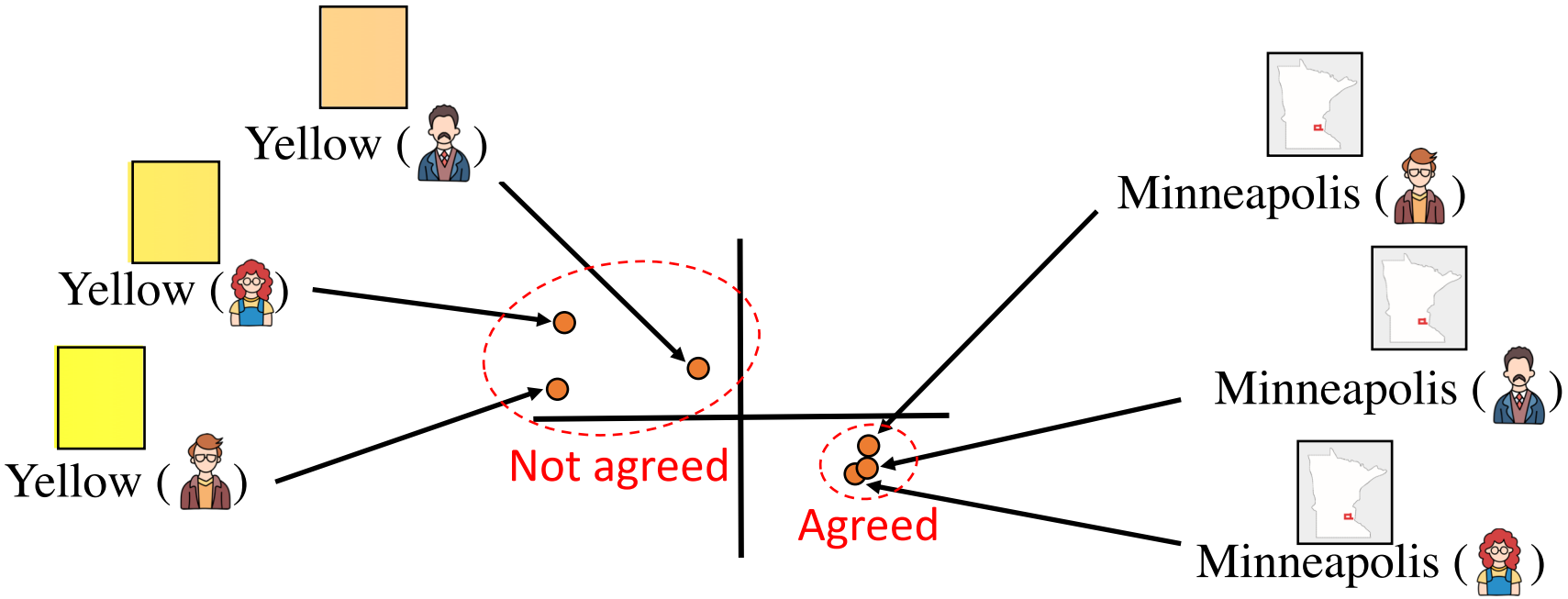
e.g. the words related to the five senses

RQ3: Common words have low personal sem. var.?

Approach

Compute word embeddings for each person

e.g., word **"Yellow"** and **"Minneapolis"**



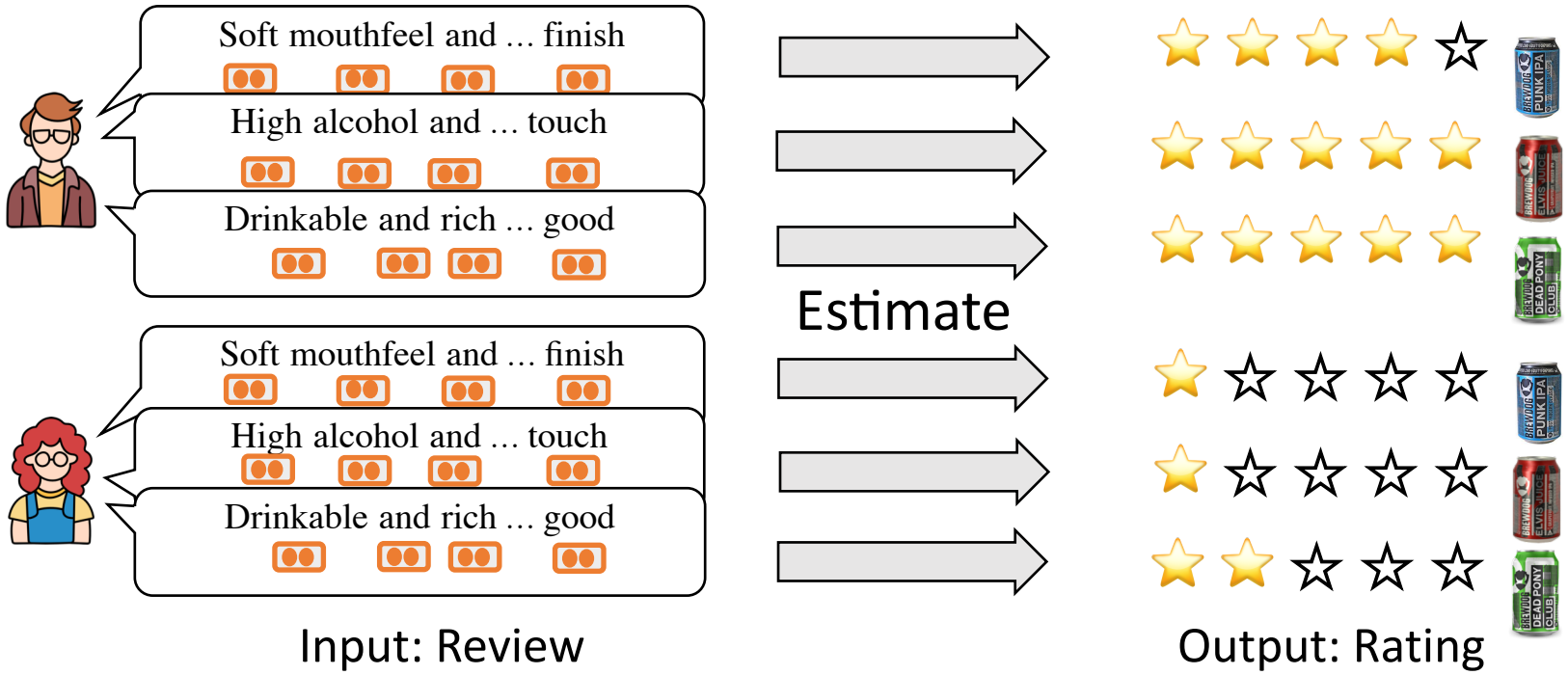
Personalized word embeddings

Existing work

Goal: Improve task performances [Tang+15, .Lin+ 17]

- Obtain personalized word emb. through the task with **subjective output**

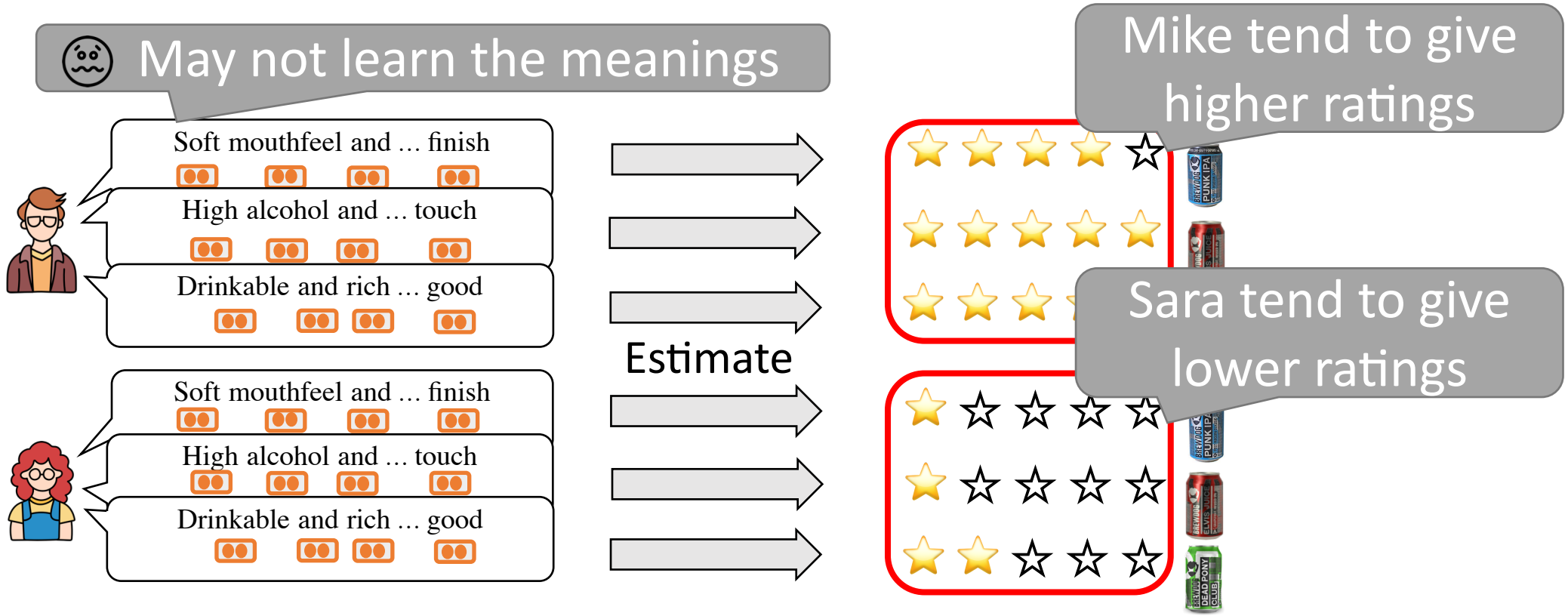
  e.g., Sentiment analysis



Problem on existing work

Bias on output due to subjectivity for each person

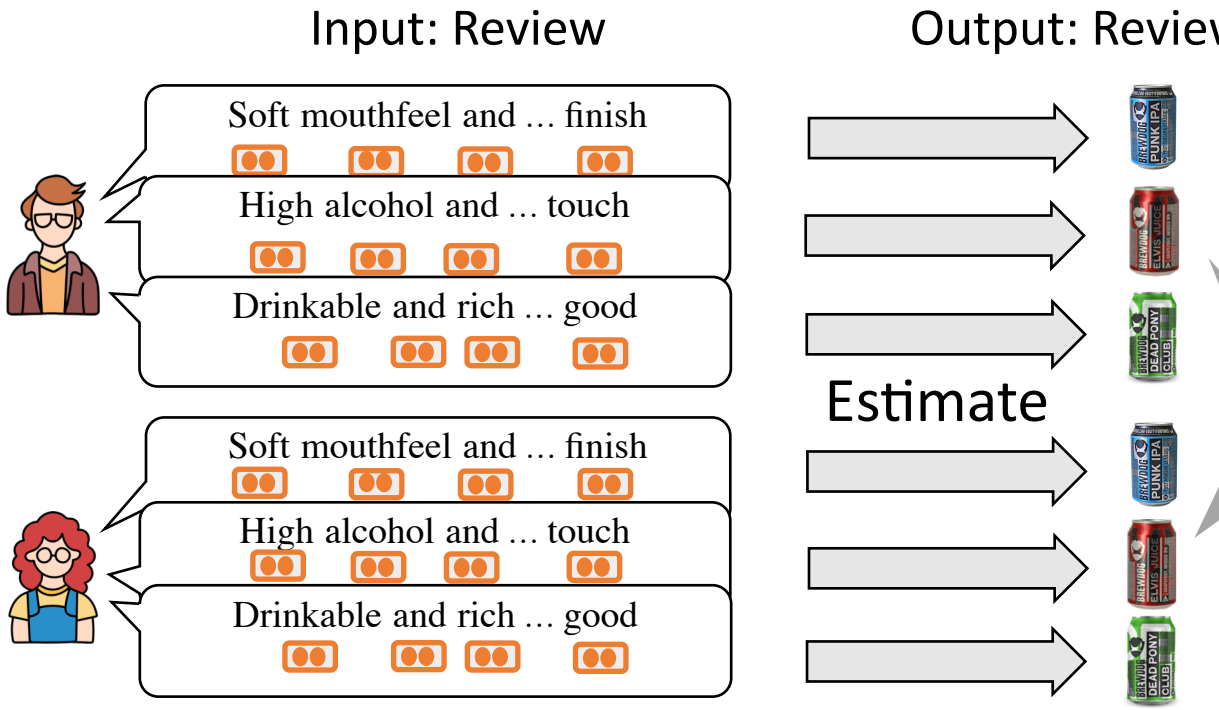
Make the task easier to solve without modeling the meanings of input words



Can not analyze personalized word emb. about their meanings

Idea: Review-target identification task

- Task setting that is difficult to solve without modeling meanings of input words (Our target)



Automatically defined before writing regardless of subjectivity for each person

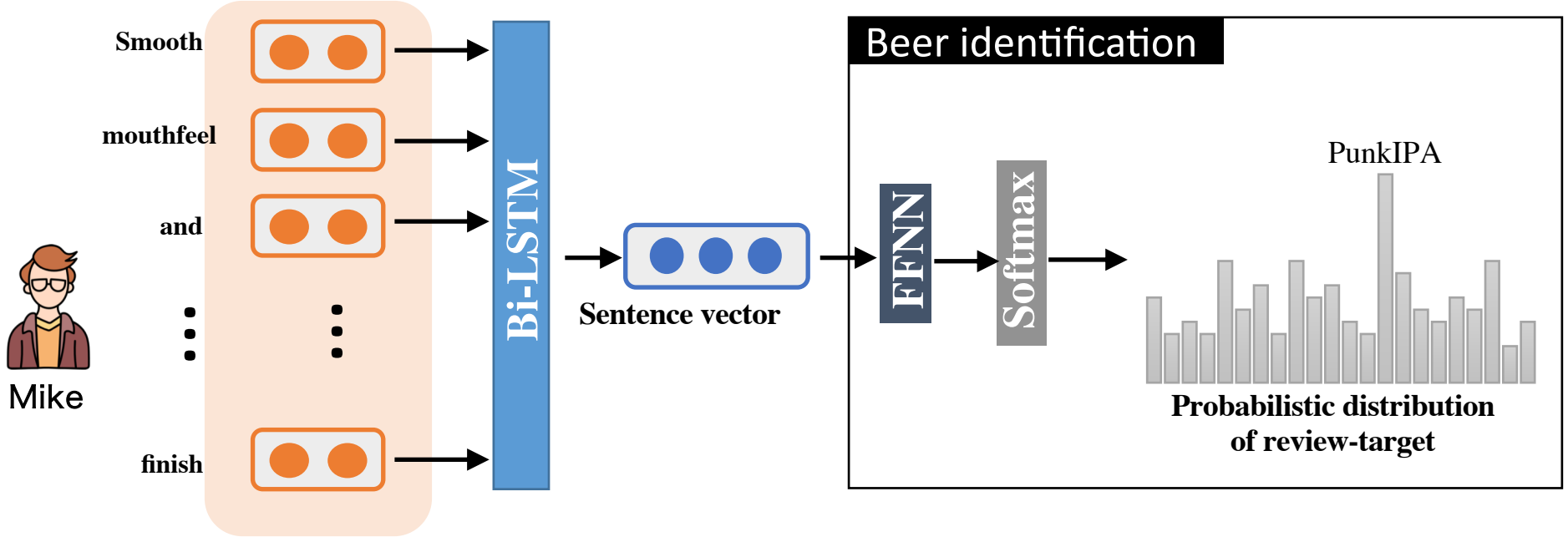
Enable personalized word emb. to be analyzed on their meanings

Overview of our method

Personalized word embeddings are jointly trained through the review-target identification task

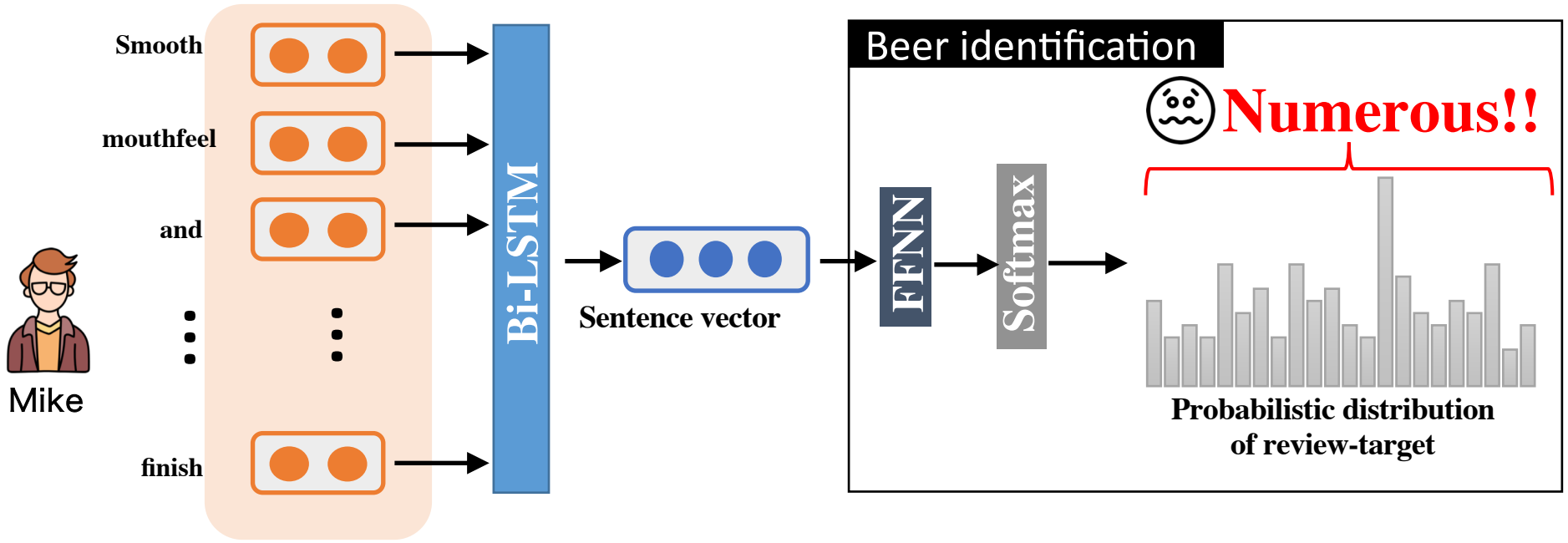
- Initialized by pretrained Skip-gram embeddings [Mikolov+ 13]

e.g., review-target: PunkIPA (Beer) 



Issue: Data-sparseness

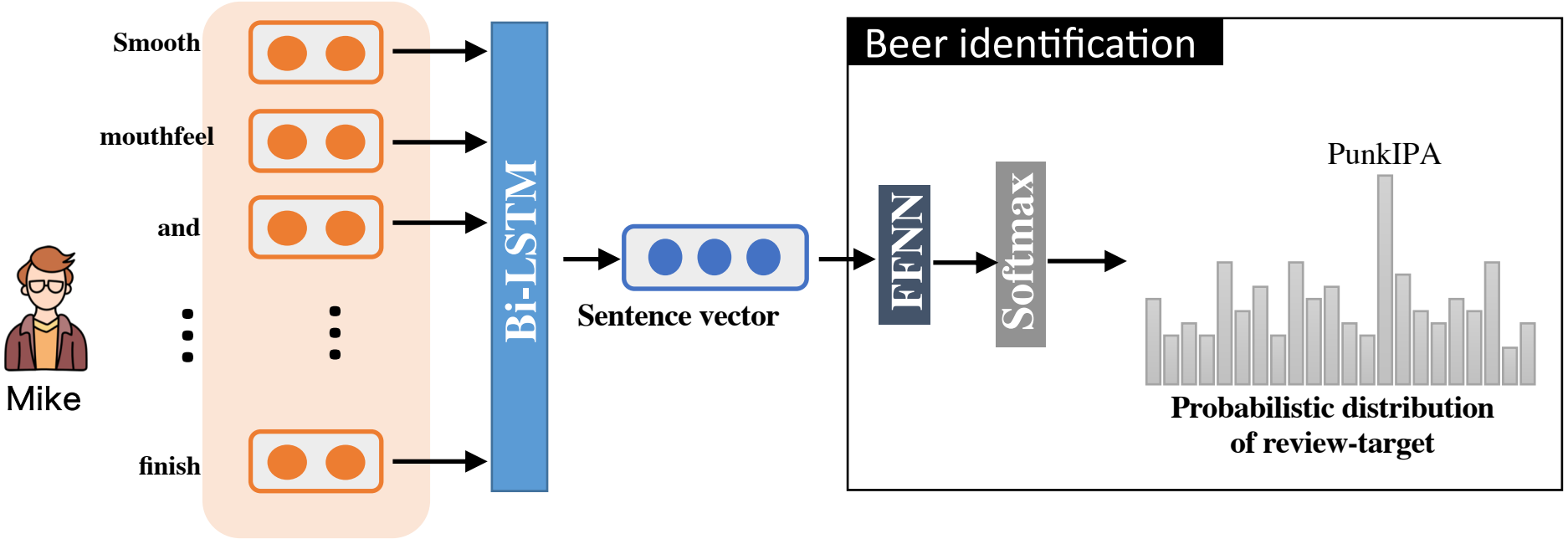
- Difficult to stably train the personalized word emb. due to the **extremely large number** of review-target
  - e.g., Amazon review data: **~10 million** [He+, 16]
    - RateBeer dataset: **~0.1 million** [McAulley+, 13]



Solution: Multi-task learning (MTL)

- Increase supervision by solving relatively easy sub-problems
  - Jointly train the metadata identification

Review-target	**Beer**	PunkIPA
Metadata	**Brewery**	Brewdog
	Style	IPA
	ABV	7.0



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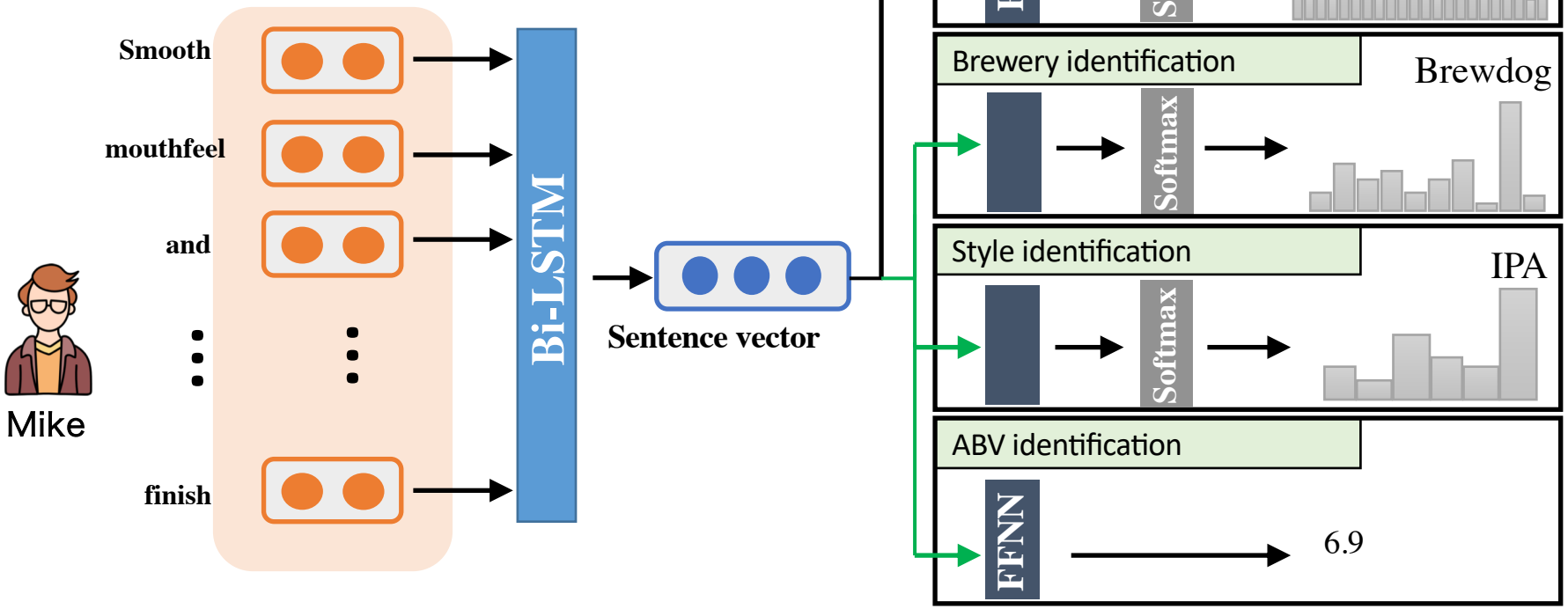


Two types of experiments

Intrinsic evaluation

- **TRAIN**: Review-target identification
- **TEST**: Review-target identification

Extrinsic evaluation

- **TRAIN**: review-target identification
- **TEST**: Sentiment analysis

Intrinsic evaluation: settings

Confirm the ability of personalized word emb. to capture meanings of the words for each person

- To successfully solve the task that can't use output bias, meanings of the input words should be ably modeled

- **Dataset**: RateBeer [McAulley and Leskovec, 13]
  - 526,857 reviews of top-100 users

Review-target	Beer (83,049 types)
Metadata	Brewery (6,208 types)
	Style (89 types)
	ABV

- **Evaluation**
  - Accuracy (%) of review-target (beer) identification

Intrinsic evaluation: result

Model	Target identification [Acc.(%)]
Majority baseline	0.03
Bi-LSTM	2.99
+ Multi-task learning with metadata	3.81
+ Personalization of word embeddings	3.32
+ ALL	**4.14**

👍Capture meanings of input words significantly better than the others ($p < 0.01$)

Can clarify **personal semantic variations** from the obtained personalized word embeddings

Extrinsic evaluation: settings and result

RQ1: Modeling personal sem. var. makes the performance of other NLP tasks better?

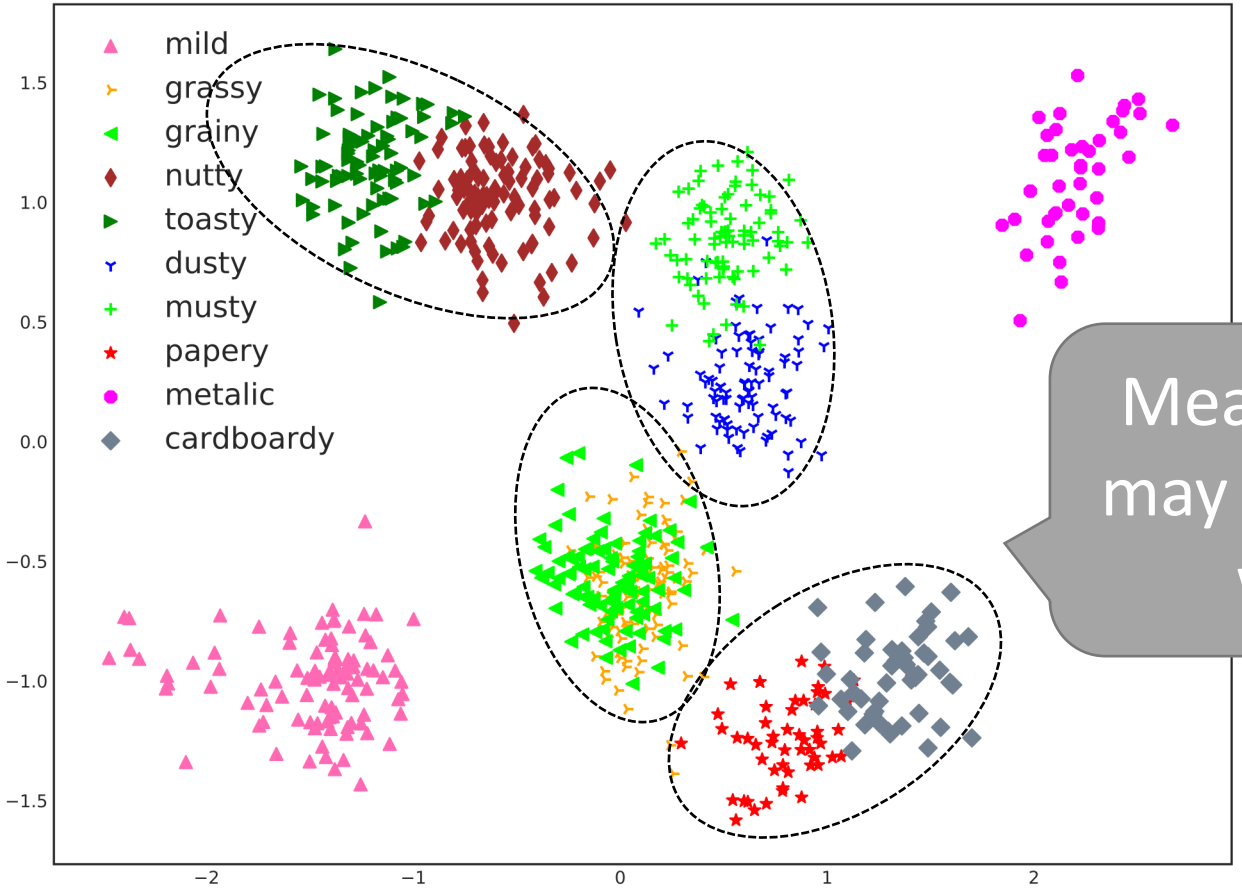
- **Task**: Sentiment analysis with regression
  - **Output**: Rating scores from 1 to 20
- **Evaluation:** Root mean square error (RMSE)

Model in which the (personalized or not) word embeddings were obtained	Sentiment analysis [RMSE]
Bi-LSTM	1.452
+ Multi-task learning with metadata	1.447
+ Personalization of word embeddings	1.406
+ ALL	**1.381**

👍Personalized word emb. capturing personal sem. var. works better also on an extrinsic task

Analysis: visualization of confused meanings

Two-dimensional representation of the obtained personalized word embeddings using PCA



Meanings of the words may be used in different ways by person

Analysis: understanding semantic variation (1)

RQ2: What kind of words have large semantic variations?

Definition of personal semantic variation

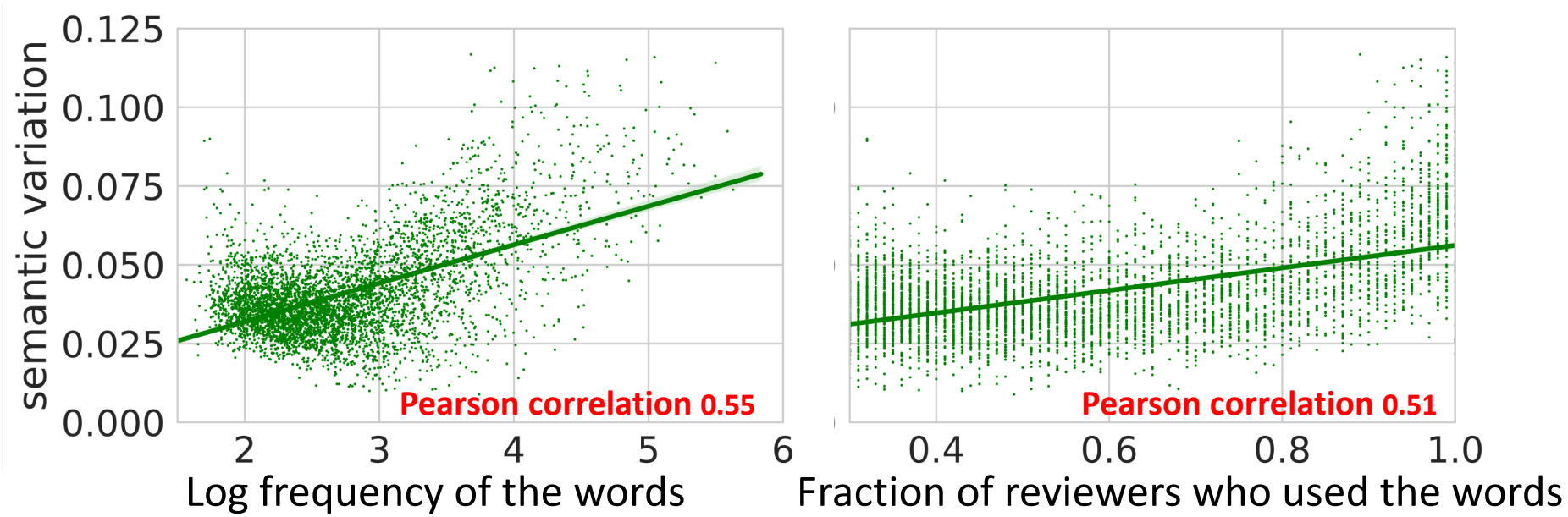
- **Variance** of the personalized word embeddings

Top -20	surprisingly, **nice**, quite, **light**, **pleasant**, actually, though, buttery, **grassy**, really, **bready**, **dusty**, **fruity**, **decent**, **mild**, rather, little, **toffee**, **earthy**, **woody**
Bottom -20	**lasted**, primary, system, **secondary**, **personal**, test, acquired, ii, **greater**, standout, roof, England, flow, scored, purchase, partly, Colorado, spare, rocks, ounce

The words related to the five senses and **adjectives** have large semantic var.

Analysis: understanding semantic variation (2)

RQ3: Common words have small semantic variations?



Even if frequently or widely used, meanings of the words are not necessarily agreed among people

- In beer review, frequent words are related to five senses

Summary

Goal: Understanding personal semantic variation

Contribution: Establish method to eliminate subjective bias on output for each person from the training process of personalized word emb.

Findings

- Adjectives and words about the five senses have large sem. var.
- Modeling semantic var. works effectively also on **extrinsic** task
- Even if the word is common, the meanings are not necessarily agreed

Future work

- Further analysis on more datasets and tasks
- Extension of our method for documents other than review text