

# MOOD CLASSIFICATION USING LISTENING DATA

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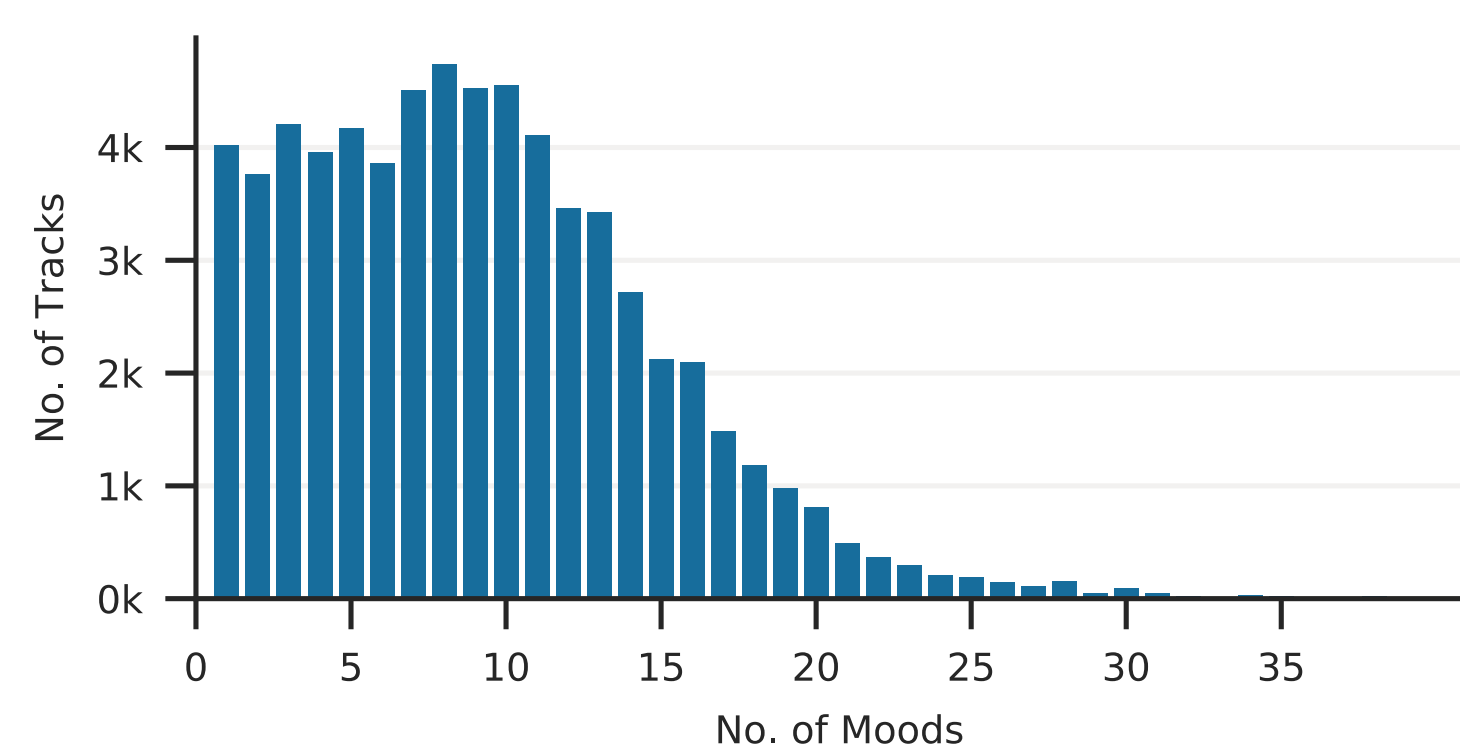
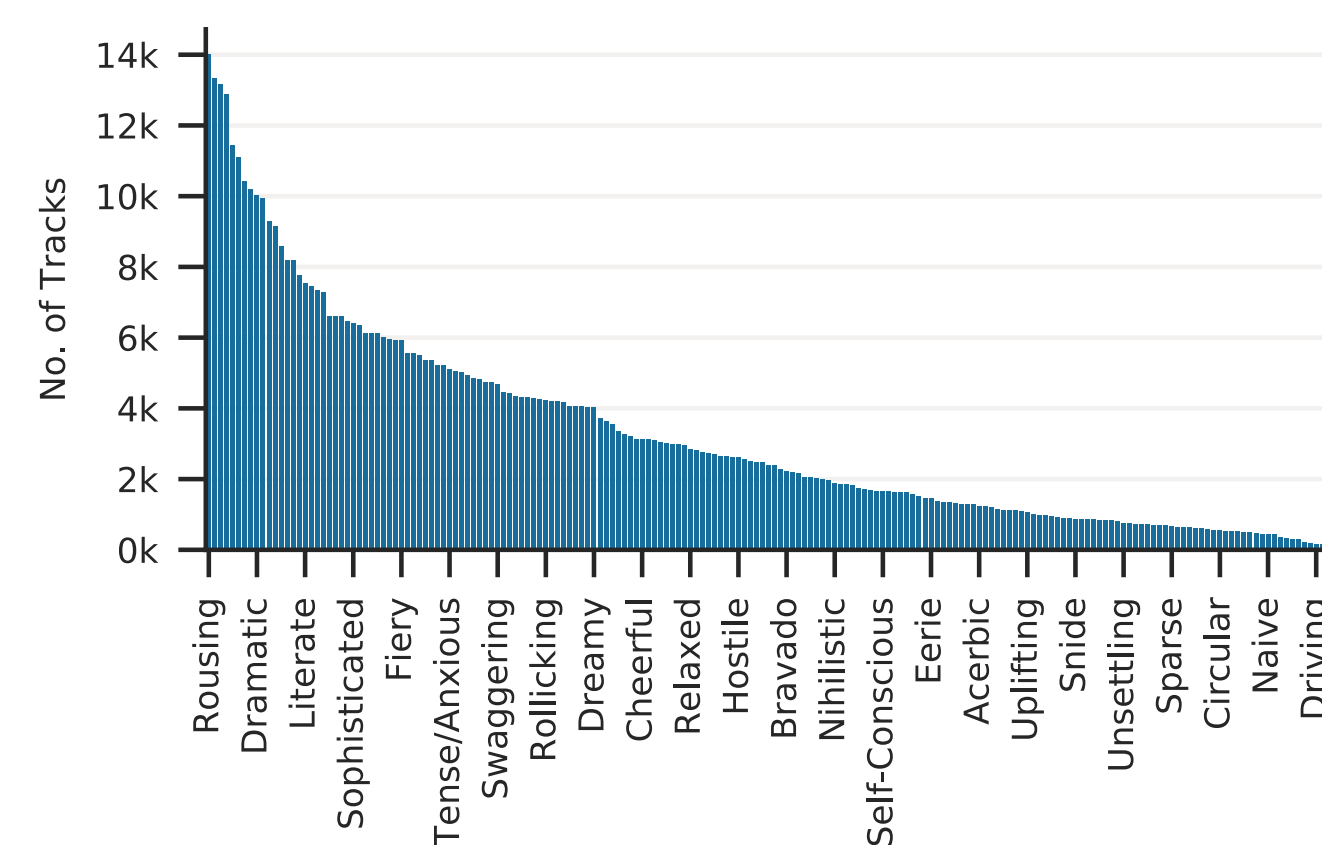
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## AllMusic Mood Subset

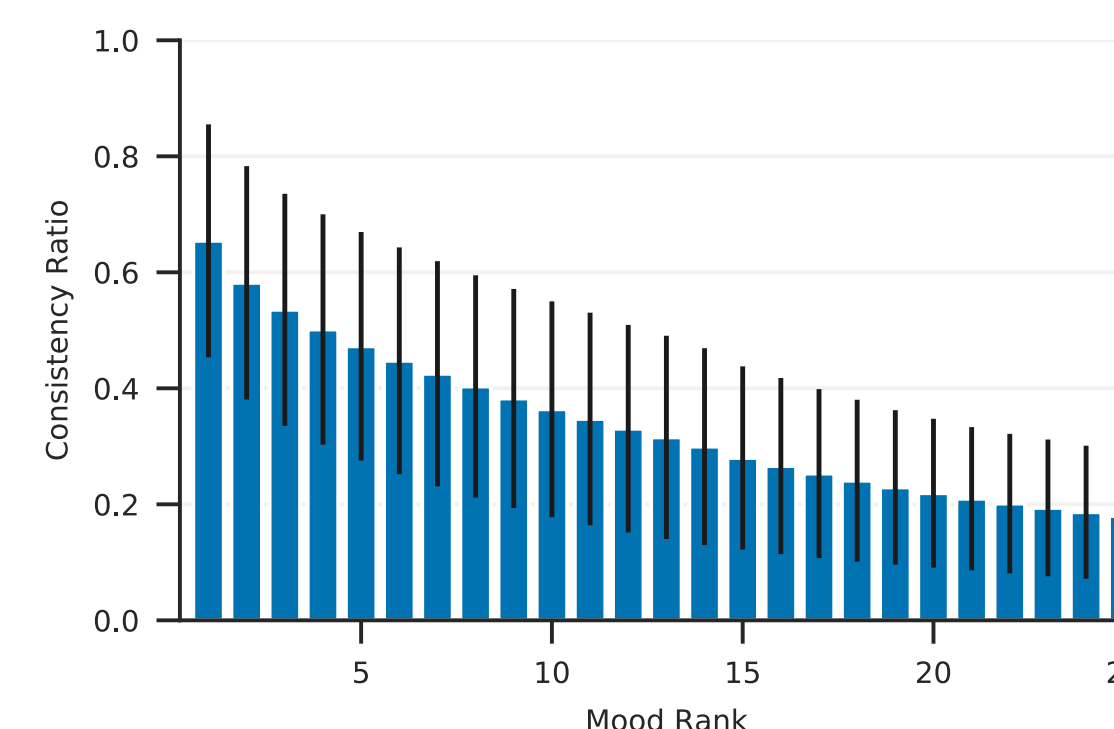
### A NEW DATASET FOR LARGE-VOCABULARY MOOD CLASSIFICATION

- Links the **Million Song Dataset** to AllMusic moods.
- 66993 tracks** in total.
- 188 different mood tags.**
- Echo Nest Taste Profile provides **listening data**.
- 7-digital audio previews provide **audio data**.
- AllMusic **mood data** is proprietary, but freely available at *allmusic.com*
- Moods are annotated on an **album level** and propagated down to tracks.

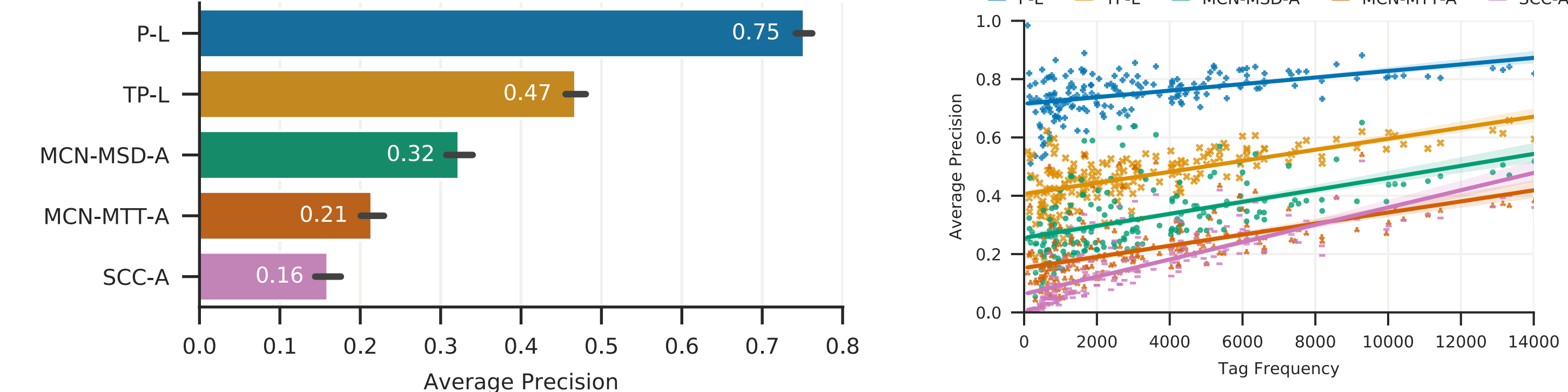


## Listening Data for Mood Classification

- The Echo Nest Taste Profile:
  - 28M play counts of 1M users and 384k tracks.**
- Observation:** users listen to music **consistent in mood: 65.4%** of all listened tracks by a user contain the **most popular mood tag** for a user.
- Thus:** listening-based embeddings could be powerful features for mood classification!



## Result: Listening Data Outperforms Audio Data

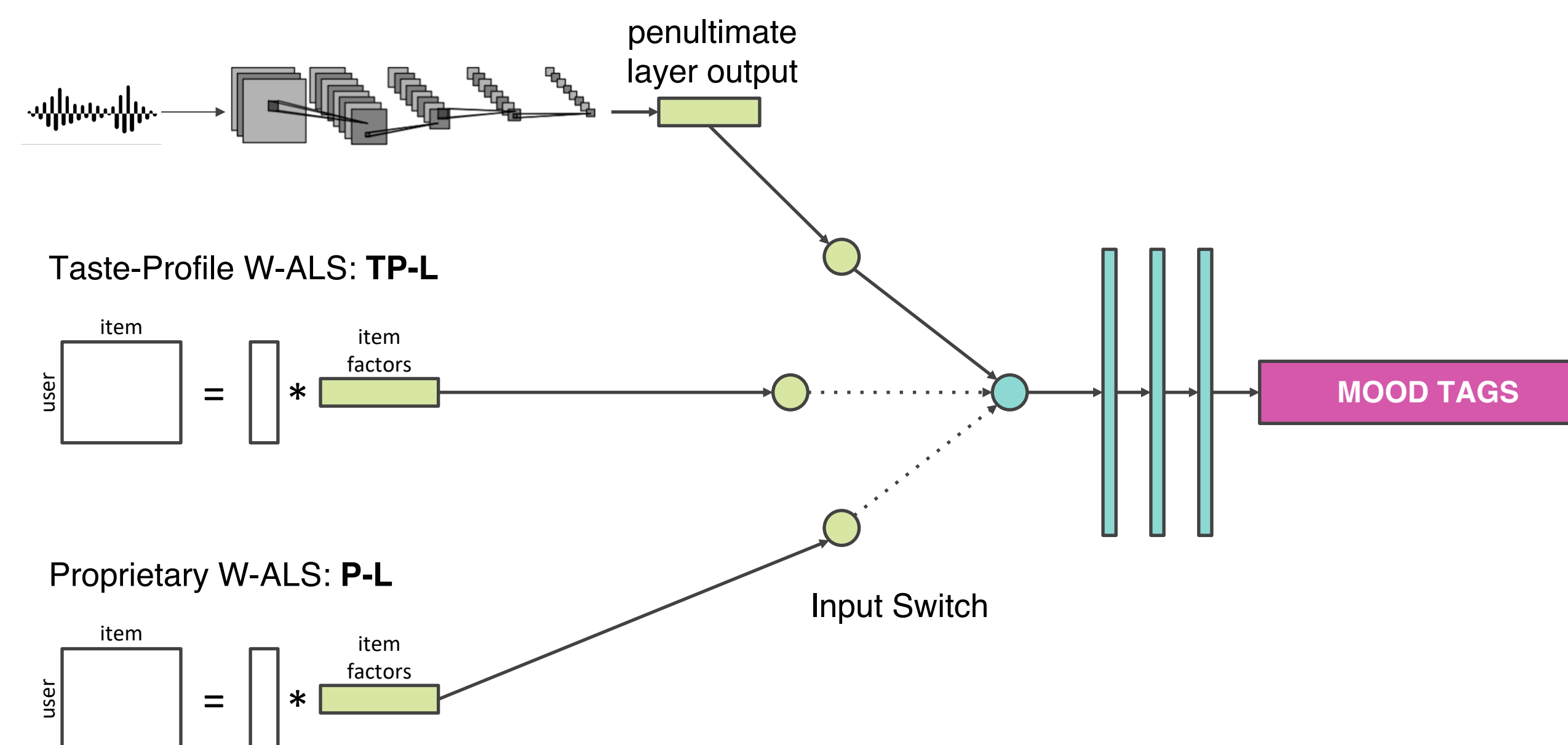


- Transfer learning** from models trained on big data **helps with rare tags.**
- Massive **explicit feedback better than implicit.**
- Tag-wise results correlate** between audio-based models, regardless of absolute results.
- Implicit vs explicit** feedback seem to capture **different listener behavioral data.**

	P-L	TP-L	MCN-MSD-A	MCN-MTT-A	SCC-A
P-L	1	0.61	0.66	0.63	0.58
TP-L	0.61	1	0.45	0.47	0.61
MCN-MSD-A	0.66	0.45	1	0.95	0.79
MCN-MTT-A	0.63	0.47	0.95	1	0.83
SCC-A	0.58	0.61	0.79	0.83	1

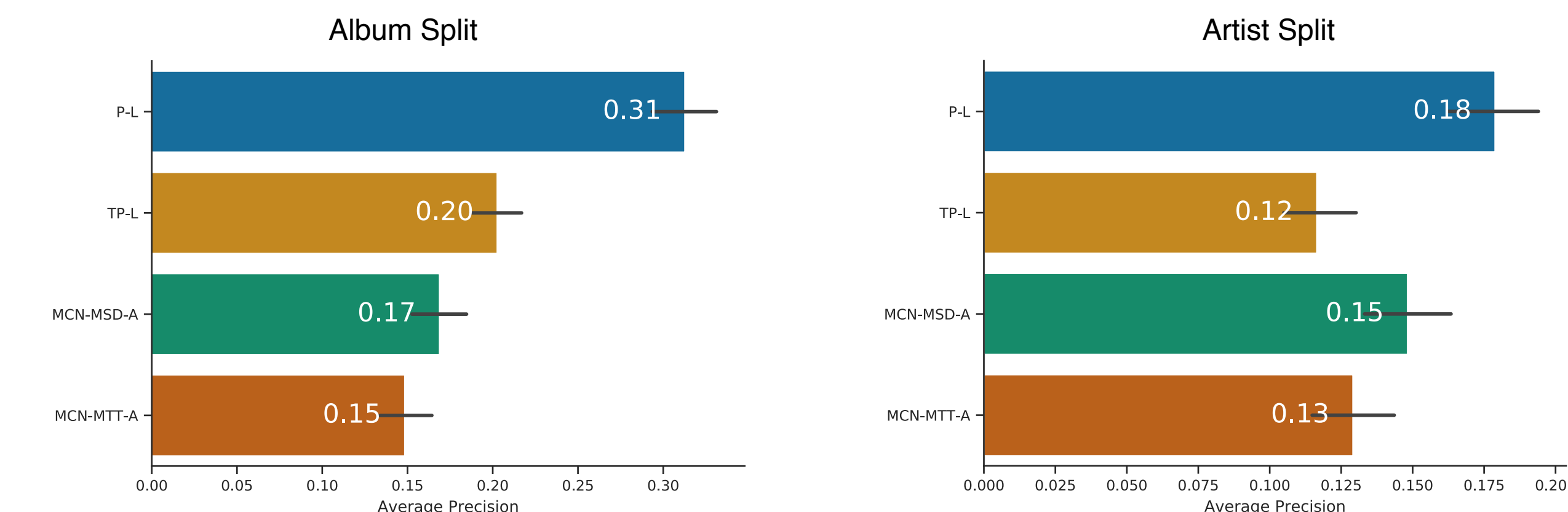
## Experiment: Transfer Learning

- Audio-based embeddings:**
  - MCN-MSD-A:** Musicnn trained on Million Song dataset
  - MCN-MTT-A:** Musicnn trained on MagnaTagATune dataset
- Listening-based embeddings:**
  - TP-L:** weighted ALS of Taste Profile interaction matrix (implicit feedback)
  - P-L:** proprietary ALS of in-house explicit feedback (> 100B thumbs)



## Chasing Confounding Factors: More Splits, More Results

- Split data **by album and by artist** and re-run experiments.



- Album-split lowers results significantly**, more so for listening-based than for audio-based embeddings.
- Artist-split further reduces results**, **Taste-Profile based embeddings lose their advantage** over audio-based ones.
- Conclusion:** Taste-Profile seems to take advantage of mood-artist correlation to achieve results; internal **explicit feedback data performs best regardless.**

**Code and Data:** <https://github.com/fdlm/listening-moods>