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SAMSUNG

Same Words, Different Tone: Genre-Specific Sentiment Lexicons for Digital Music Reviews

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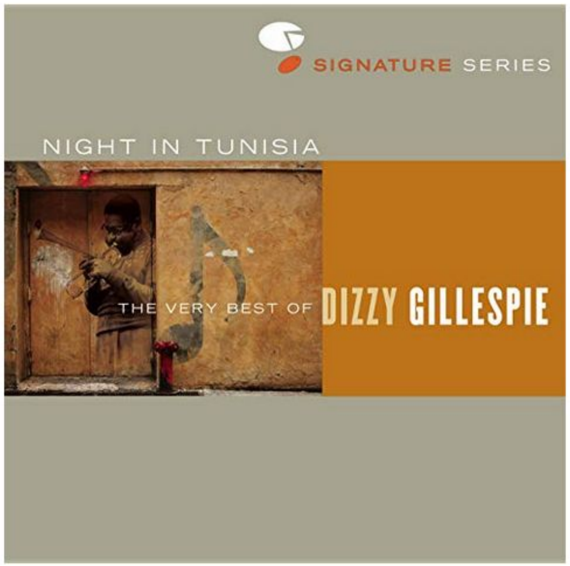
Third International Workshop on Language, Music and Computing
St. Petersburg, Russia
16-18 Dec 2019

a total of 17 slides

Research domain: online reviews as *amateur music critique*



Night In Tunisia: The Very Best Of Dizzy Gillespie
Dizzy Gillespie
July 31, 2006

10 ratings

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Dl
It really surprise me!!!!!
May 7, 2014
Format: Audio CD | Verified Purchase
I heard a song of Gizzie Gillispie in a Chicano class, and I liked, so I look for a cd that had like with the best songs to listen more themes about him, and it is amazing!!!! I even bought a second cd as a gift to my boyfriend.
One person found this helpful
Helpful | Comment | Report abuse

Frank J. Altschul
satisfyinglydizzy
November 29, 2009
Format: Audio CD | Verified Purchase
Perfect if you need at least one Dizzy in your collection. Very balanced and very rich.
8 people found this helpful
Helpful | Comment | Report abuse

Musicman
A Good Collection
April 20, 2012
Format: Audio CD | Verified Purchase
I like this CD of Dizzy Gillespie's material. This is only the second album of Dizzy's stuff that I have purchased. It is a good collection of the important material from his career ranging from his Be Bop era to his Afro-Cuban era. I enjoy most "Night in Tunisia" and "Manteca" which are probably his most well known songs. The reason I did not give this a higher rating is because the CD came with no liner notes except the names of the songs. While it offers a collection at a cheaper price, it lacks the quality of other collections that have important liner notes about the dates of the recordings and the band members that played with Dizzy. This is unfortunate and makes this CD not the best purchase for jazz enthusiasts that want to not just hear a recording, but also learn about the musicians who made it.
9 people found this helpful

Online stores reviews are valuable

- for the stores' goods promotion
- for customers' decision making
- for popular music research
- for curious linguists

Typical data sample

J. McAuley and J. Leskovec. Hidden factors and hidden topics: understanding rating dimensions with review text. RecSys, 2013.

{
"reviewerID": "A3Q1J7VFGG80EK",
"asin": "5555991584",
"reviewerName": "Amber",
"helpful": [0, 0],
"reviewText": "I'm not a huge, know it all Enya fan. But I do like her music very much. Of the few CD's I've heard by Enya, this is my favorite. I LOVE the song Anywhere Is (track 2). It is pleasent and uplifting. It makes me smile and want to twirl in circles. Maybe this doesn't help anyone else want to buy the CD, but if you need some incentive: the CD is soothing and light to listen to. It would be a great CD to buy if that is the type of thing you are looking for.",
"overall": 5.0,
"summary": "Memory of Trees or My favorite Enya CD",
"unixReviewTime": 975628800,
"reviewTime": "12 1, 2000"
}

{"reviewerID": "A1REP2FMPOXV4A",
"asin": "5555991584",
"reviewerName": "Andrew G.",
"helpful": [6, 8],
"reviewText": "This is my very favorite Enya album to date. Even writing a review of it will not come close to my inner feelings about its music. The first song, the title track "The Memory of Trees", is the most beautiful song I've ever

Research questions and motivation

(Q1) is it true that there is a significant **difference in sentiment polarity** of certain words in reviews on different genres of music?

(Q2) if so, to which extent this difference can be estimated with data-based approaches?

Note: we do not have any annotated [in terms of differing semantics] data related to the task

Relevant prior work

Yang Yi, Eisenstein Jacob
Putting Things in Context: Community-specific Embedding Projections for Sentiment Analysis. 2015.

Rothe Sascha, Ebert Sebastian, Schutze Hinrich
Ultradense Word Embeddings by Orthogonal Transformation. 2016.

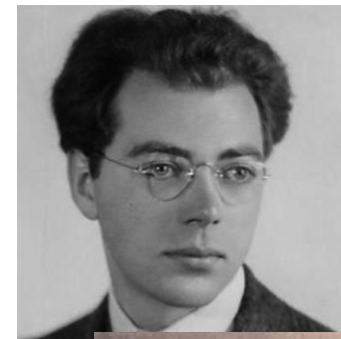
William L. Hamilton, Kevin Clark, Jure Leskovec, Dan Jurafsky
Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora. 2016.

The last work seems to be the most suitable for the low-resource setting
[for training word embeddings]

Word vectors based on distributional hypothesis

- Zellig S. Harris:
  "oculist and eye-doctor... occur in almost the same environments",
  "If A and B have almost **identical environments**. . . we say that they are synonyms"

- John Firth: **You shall know a word by the company it keeps!**



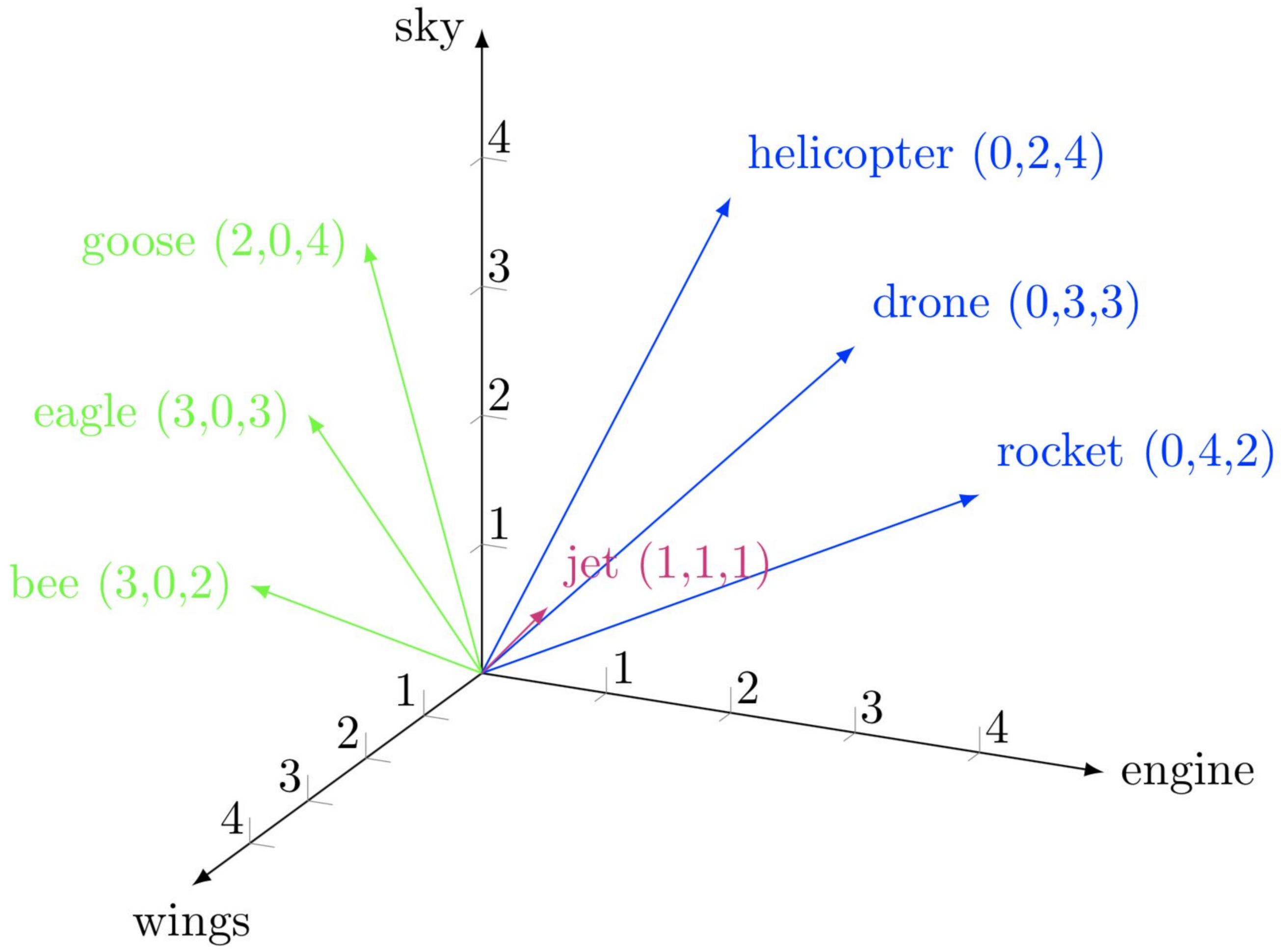
When annotation is expensive/impossibe, we can arguably judge by proxy objects, e.g. by word embeddings trained on our data

Popular models: PMI matrices, TDM+SVD, PPMI+SVD, …,
NeuralLM [Bengio et al. 2003], …, word2vec [Mikolov et al. 2013],
GloVe [Pennington et al. 2014],
fastText [Bojanowski et al. 2016], etc.

Harris, Z. S. (1954). Distributional structure. Word, 10, 146–162. Reprinted in J. Fodor and J. Katz, The Structure of Language, Prentice Hall, 1964
Z. S. Harris, Papers in Structural and Transformational Linguistics, Reidel, 1970, 775–794

Firth, J. R. (1957). A synopsis of linguistic theory 1930– 1955. In Studies in Linguistic Analysis. Philological Society. Reprinted in Palmer, F. (ed.) 1968. Selected Papers of J. R. Firth. Longman, Harlow

Word vectors based on distributional hypothesis



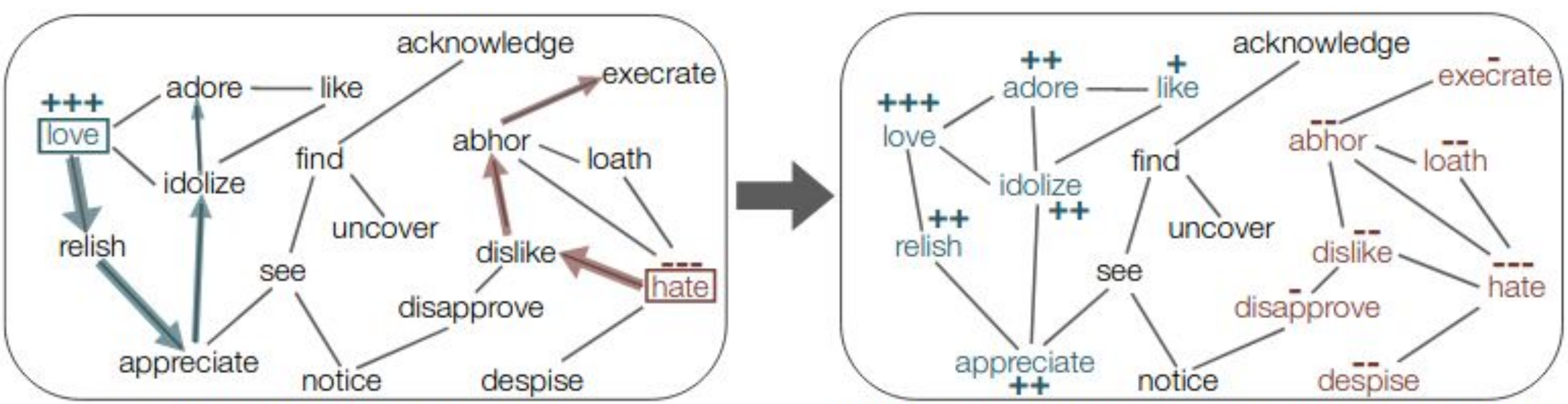
https://corpling.hypotheses.org/495

SentProp, in detail

1. Train word vectors model (PPMI+SVD, word2vec, etc.)
2. Select the vectors of words of interest
   (known lexicon/most common)
3. Build a word graph:
   a. for each node, edges connect **k** nearest neighbors
      (for corresponding vectors)
   b. each edge is assigned a weight
      (cosine similarity arccos ~ an angle between vectors)

$$\mathbf{E}_{i,j} = \arccos\left(-\frac{\mathbf{w_i}^\top \mathbf{w_j}}{\|\mathbf{w_i}\|\|\mathbf{w_j}\|}\right)$$

4. Set ‘positive’ and ‘negative’ seed words...



a. Run random walks from seed words.

b. Assign polarity scores based on frequency of random walk visits.

SentProp, in detail

5. execute a **random walk procedure:**
   transition probabilities ~ weights on edges
   a fixed probability of a “random hop” **to the vertices of a seed set**.

The resulting “random walker visits ratio” = polarity score

$$\mathbf{E}_{i,j} = \arccos\left(-\frac{\mathbf{w_i}^\top \mathbf{w_j}}{||\mathbf{w_i}||\,||\mathbf{w_j}||}\right)$$

Computing transitions scores

$$\mathbf{T} = \mathbf{D}^{\frac{1}{2}}\mathbf{E}\mathbf{D}^{\frac{1}{2}}$$

Scaling transition scores

$$\mathbf{p}^{(t+1)} = \beta\mathbf{T}\mathbf{p}^{(t)} + (1-\beta)\mathbf{s}$$

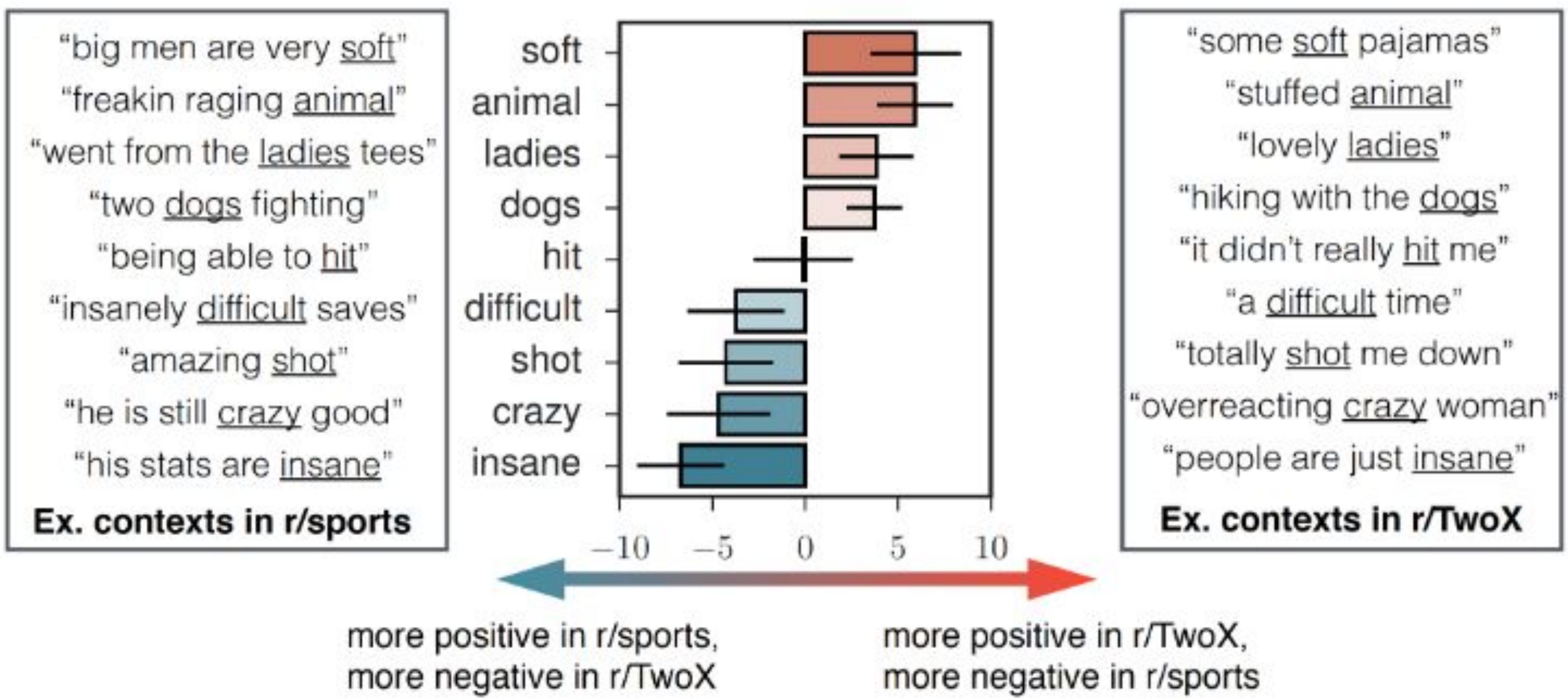
Iteratively updating polarity scores:
- beta = “random hop” chance
- s = vector, non-zero at seed words coords

$$\frac{\mathbf{p}^P(w_i)}{\mathbf{p}^P(w_i)+\mathbf{p}^N(w_i)}$$

Final polarity estimates, later scaled to have zero mean and unit variance

SentProp findings, Reddit

r/TwoXChromosomes: women's perspectives, gender issues
r/sports: sport-related discussions



Our approach: data

- Amazon Digital Music dataset [He and McAuley, 2016]

- popular music genres: Rock,Classic Rock, Alternative Rock, Jazz, Pop, R&B and Rap&Hip-Hop

- tokenizing and lemmatizing reviews with TweetTokenizer and WordNetLemmatizer of NLTK [Bird et al., 2009]

Genre	Reviews	Sentences	Lemmas
Alternative Rock	65801	454155	8175511
Dance & Electronic	17676	123178	2188057
Hard Rock & Metal	20774	159656	2843800
Jazz	10266	62435	1158296
Pop	53513	363143	6497085
Rap & Hip-Hop	39432	297439	5050967
R&B	36000	233764	4077655
Rock	47774	335467	6061372
Total	291236	2029237	36052743

Our approach: experimental setting

- experiments are similar to those described in [Hamilton et al., 2016]
  - word2vec (SGNS) [Mikolov et al., 2013] with **gensim** [Řehůřek and Sojka, 2010]: 50 dimensions for 10 iterations, 4 for half-window, minimum of 10 occurrences
  - **most frequent 5100** lemmas (for graph construction)
  - removed stopwords using NLTK [Bird et al., 2009]
  - the nearest neighbors graph: nn = 5 for each lemma
  - 10+10 **Twitter seeds** from [Hamilton et al., 2016]

Twitter	love, loved, loves, awesome, nice, amazing, best, fantastic, correct, happy	hate, hated, hates, terrible, nasty, awful, worst, horrible, wrong, sad

  - probability of a “random hop to the seed set” β equal to 0.9

- **confidence scores** via bootstrap:
  50 runs starting from 6 pos. and 6 neg. seeds (out of 10)

- heuristic: transition probabilities between pos. and neg. seeds = 0

- for analysis retained only the words from the lexicon [Hu and Liu, 2004], this resulted in 521 words for analysis.

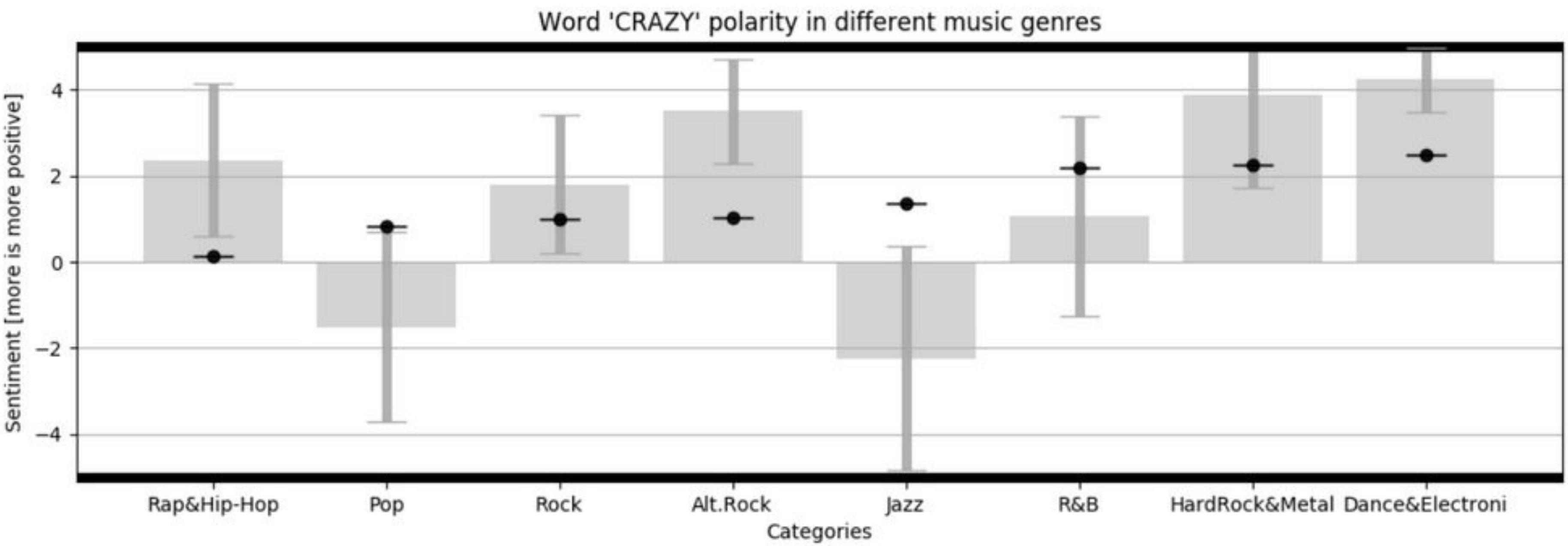
Results from bird’s eye view

- despite the ‘small’ dataset’s size, word2vec yielded best-interpretable vectors (unlike in the original work by Hamilton et al.; tried GloVe, PPMI+SVD)

- hard to obtain good estimates for most words (different bootstrap runs yield large variance for most words)

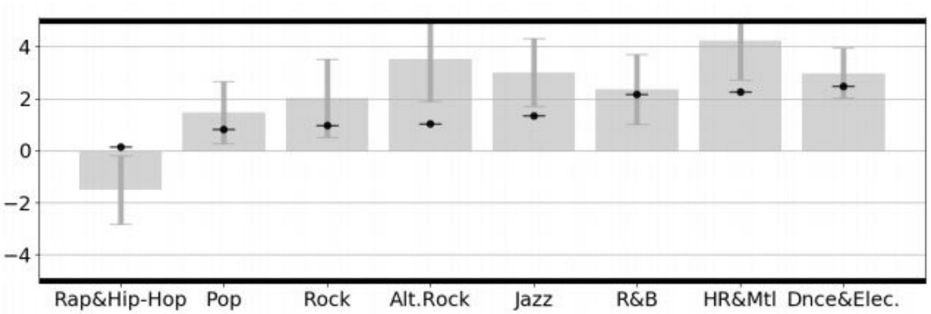
- words with low variance of the scores are arguably interpretable (in the slides: all those that have at least one of opposite score)

Findings

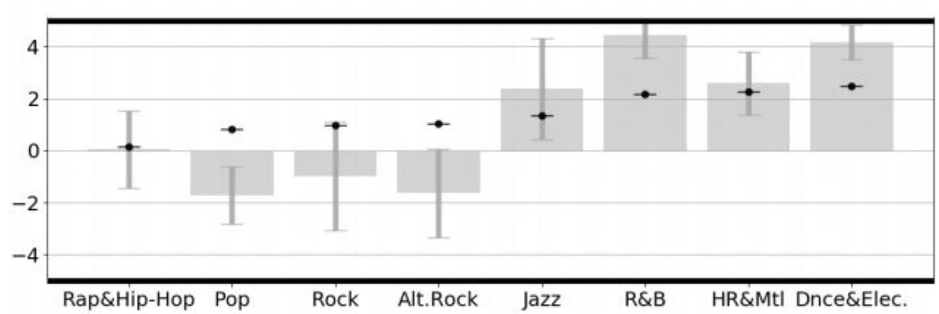


Despite low confidence in the scores, at least in Alt. Rock, HardRock&Metal and Dance&Electronic reviews this word has strictly positive sentiment, while in texts describing other genres it is usually neutral or even negative.

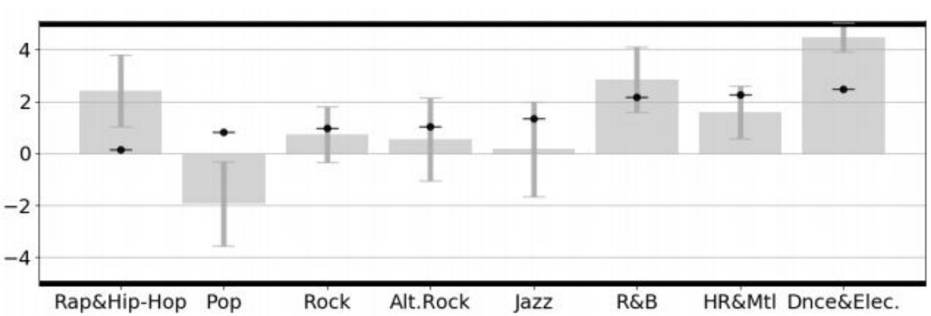
Findings



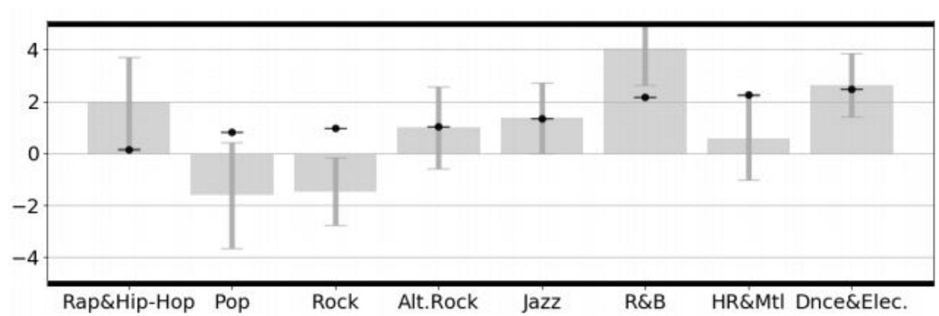
(a) Attack



(b) Freedom



(c) Heaven



(d) Hot

Interestingly, the word “hot” is positive with high confidence in reviews discussing R&B and Dance&Electronics = “excited”? = “sexy”?

The word “attack” is nonnegative everywhere but Rap&Hip-Hop reviews
= “the act or manner of beginning a musical tone or phrase”?

Conclusion, future research

- the overall approach looks promising

- probably need more data? or some other way to use it (augmentations tricks?)

- contextual embeddings [e.g. ELMo, BERT, etc.]?

Thank you for your attention!

Q&A

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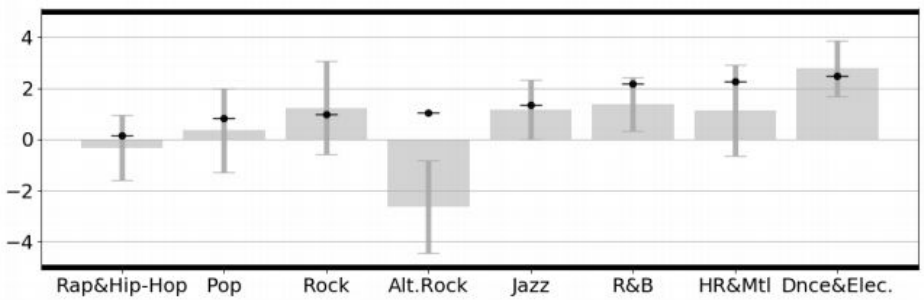
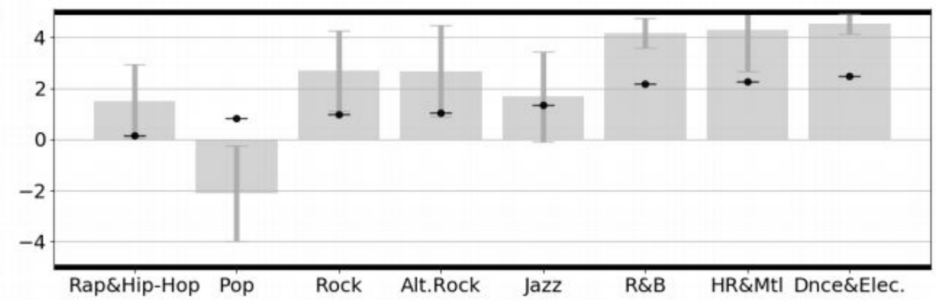
The slides will be made available through https://**alexeyev**.github.io/
Images, if not stated otherwise, are from the SentProp paper.

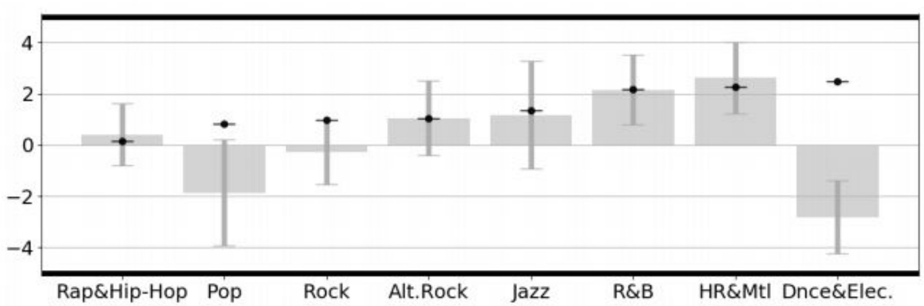
Findings



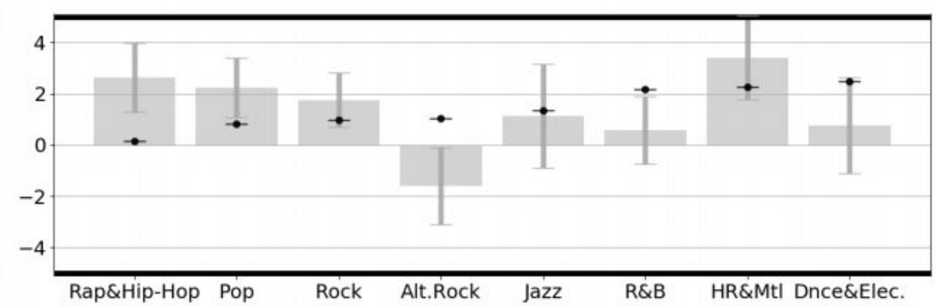
(e) Idol



(f) Softer



(g) Suffered



(h) Unfortunate

Rock/R&B musicians definitely do like to suffer