Determination of the Number of Topics Intrinsically: Is It Possible?

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He tethered his horse, which had begun to shiver; fed it; and threw a light blanket over its hindquarters against the chill. He kindled a small fire and prepared a meal, then sat down to wait out the mist, taking up the eastern gourd and composing to its eery metallic tones a chanted lament. The mist coiled around him, sent cold, probing fingers into his meagre shelter. His words fell into the silence like stones into the absolute abyss: ‘Strong visions: I have strong visions of this place in the empty times… Far below there are wavering pines… I left the rowan elphin woods to fulminate on ancient headlands, dipping slowly into the glasen seas of evening…’

(*The Pastel City by M. John Harrison*)

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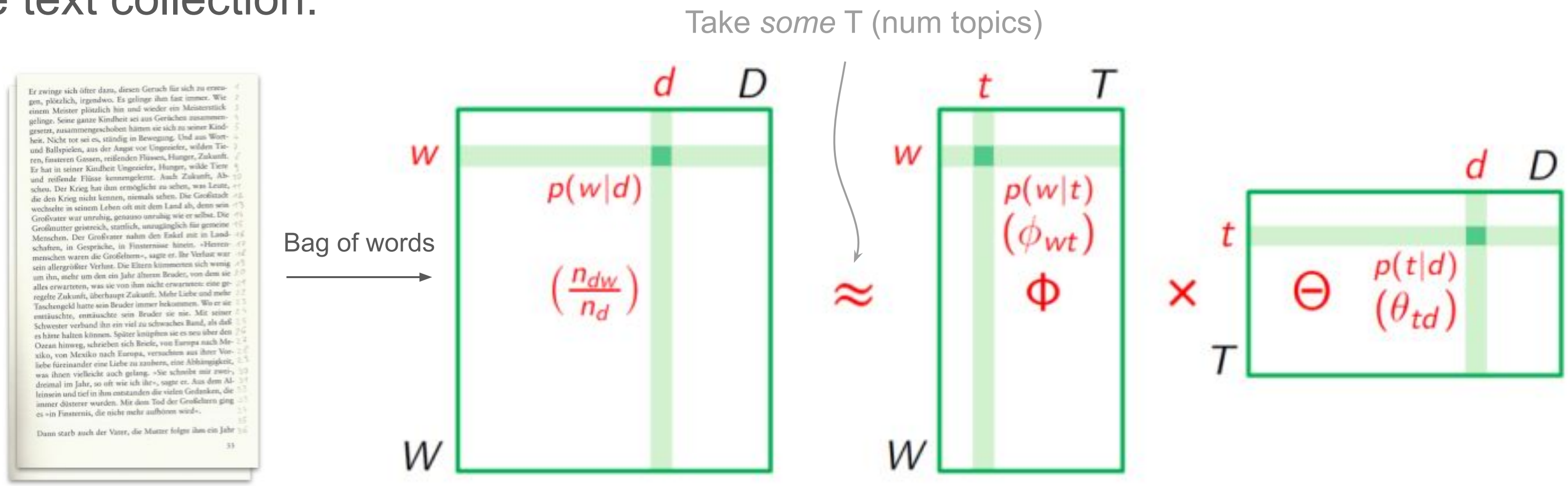
Animals	**Autumn**	**Camp**	**Music**	**Horror**	**Mystery**	**Nature**	p(w | t)
cat	cold	fire	song	eery	fate	wood	
dog	mist	warm	guitar	lament	ancient	sky	
horse	chill	shelter	tone	abyss	artifact	sea	
wolf	evening	safe	string	silence	cards	pine	
hay	shiver	meal	compose	empty	forget	stone	
fish-hawk	metallic	kindle	chant	meagre	vision	rowan	
hindquarters	glasen	gourd	ballad	rustle	elphin	headland	

Topic Modeling

Topic modelling assumes that there are a number of *latent topics* which explain the text collection.



Text collection D (num docs), W (vocab size)	Matrix of word-in-document relative frequencies	Matrix of word-in-topic probabilities	Matrix of topic-in-document probabilities

Input

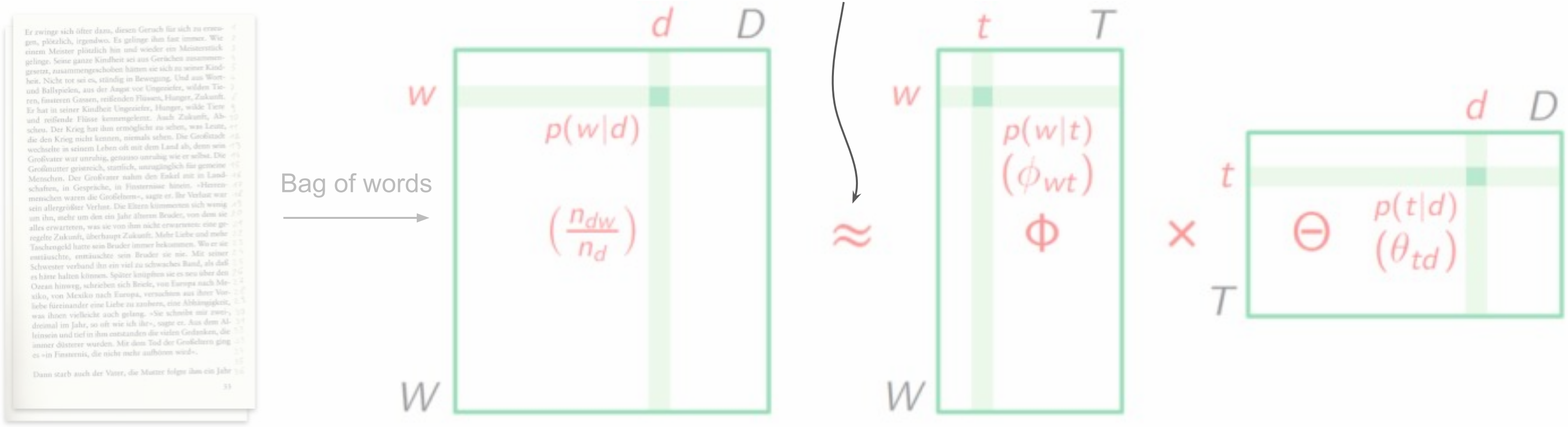
Output

Konstantin Vorontsov, [Probabilistic Topic Modeling] (in Russian).

Topic Modeling

Topic modelling assumes that there are a number of *latent topics* which explain the text collection.

Take *what* T (num topics)?



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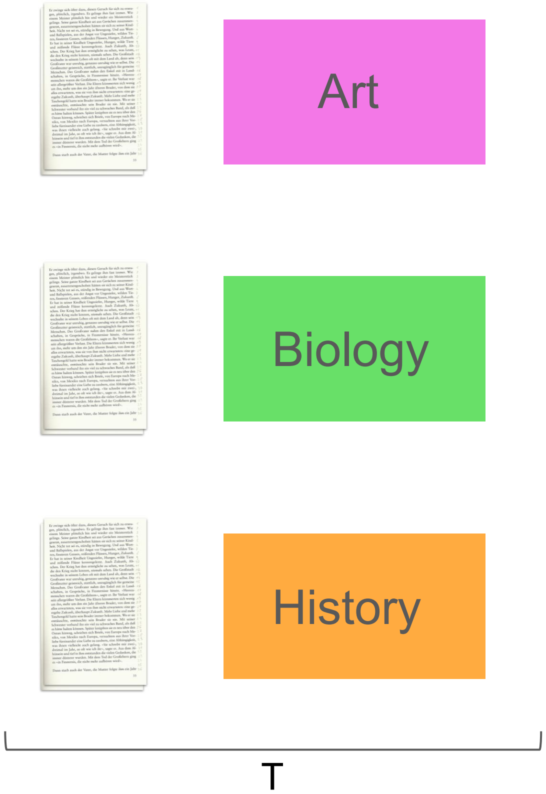
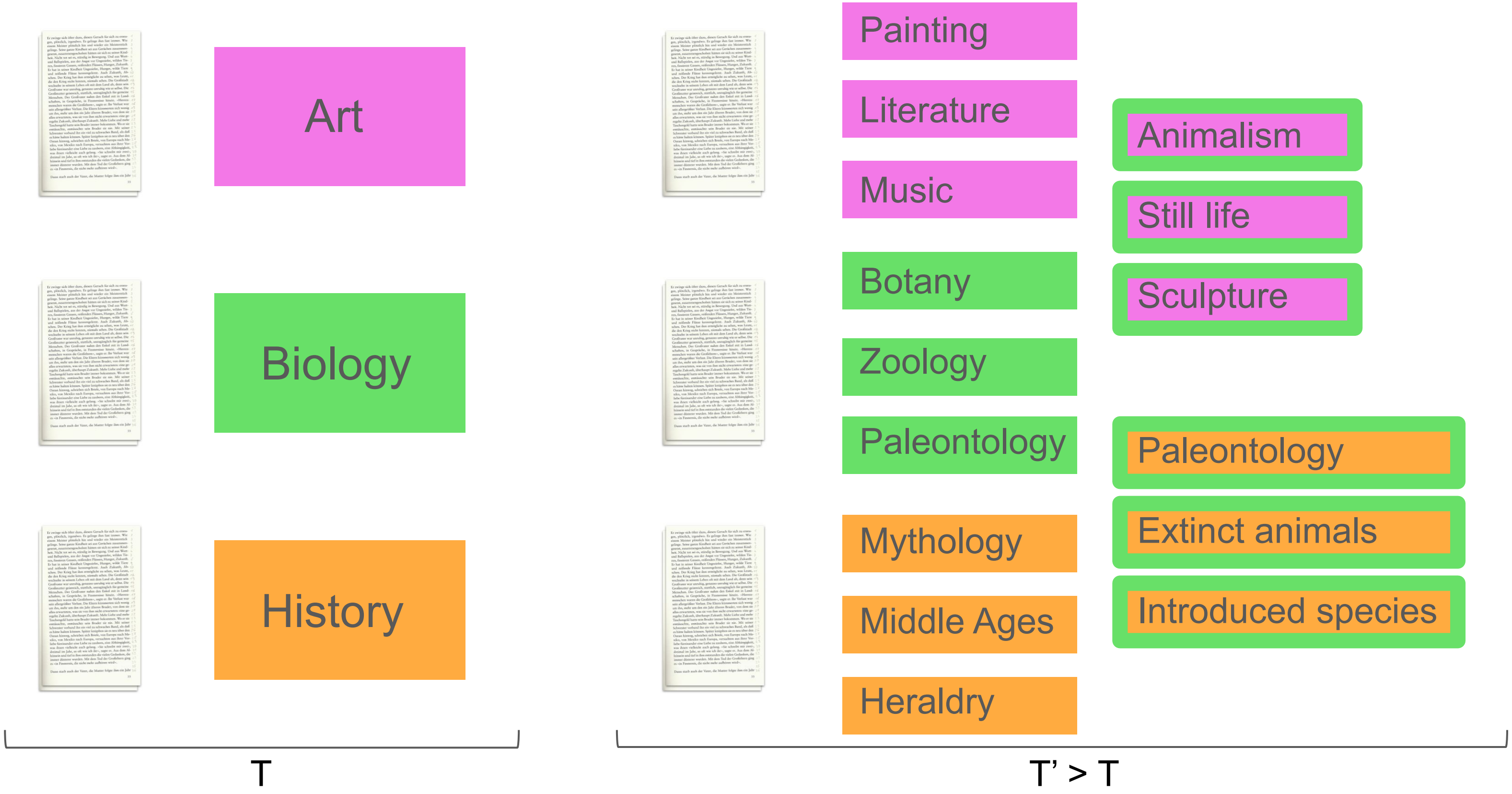


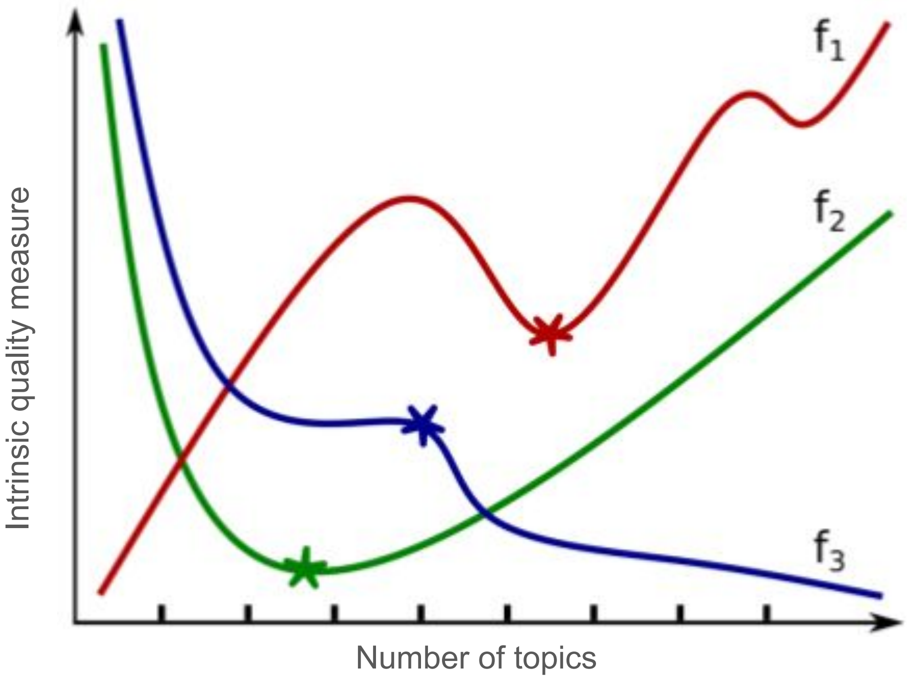
Number of Topics?



Determination of the Number of Topics Intrinsically

Purpose: find out if intrinsic model quality criteria help in determining the number of topics.

Solution: train models with different number of topics and select the optimal number as corresponding to the best quality.



Expected possible dependencies of the intrinsic quality criterion on the number of topics.

Related Work

- ldatuning

  Perplexity, topic diversity for LDA.

- TOM

  Topic diversity, topic model stability.

- OCTIS

  Topic diversity, coherence but without determining the number of topics.

Nikita M., Chaney N. Ldatuning: Tuning of the latent dirichlet allocation models parameters. – 2016. (github)
Guille A., Soriano-Morales E. P. TOM: A library for topic modeling and browsing. – 2016. (github)
Terragni S. et al. OCTIS: Comparing and optimizing topic models is simple! – 2021. (github)

Intrinsic Quality Measures

- **Perplexity** (↓)

  Measure of model's "surprise" when it sees text.

- **Diversity and sufficiency** (*D-avg-COS, D-Spectral*; ↑)

  If the number of topics is too large, the model produces a lot of small similar topics.

- **Clustering** (*SilhC, CHI*; ↑)

  How similar an object (word) is to its own cluster (topic) compared to other clusters.

- **Stability** (↓)

  Models with the "incorrect" number of topics are unstable (differ from each other).

https://github.com/machine-intelligence-laboratory/OptimalNumberOfTopics

Intrinsic Quality Measures

- **Information-theoretic** (*AIC, BIC, MDL*; ↓)

  Balance between model complexity and the goodness of fit
  ("model complexity minus model likelihood").

- **Entropy** (*Rényi*; ↓)

  "Correct" number of particle states (word topics) should correspond to the equilibrium state, which is characterised by the minimum of entropy.

- **Top-tokens**

  Nonrandomness (*Coherence*; ↑) and specificity (*Lift*; ↑) of topic top words.

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Methodology

```
FOR EACH dataset:
    FOR EACH topic_model:
        FOR EACH random_seed:
            FOR EACH t FROM t_min(dataset) TO t_max(dataset):
                init(topic_model, random_seed)
                train(topic_model, t)
                quality = eval(topic_model)
                draw_on_plot(t, quality)

            t_opt = analyze_plot()  # search for pronounced min/max
```

Models

- **PLSA**: a simple topic model without any hyperparameters aside from T.
- **LDA**: a well-known topic model, having priors for Φ and Θ distributions.
- **Decorrelated** (ARTM): attempts to reduce pairwise topic correlations.
- **Sparse** (ARTM): divides its topics into background and specific (sparse).
- **Sparse decorrelated** (ARTM): sparse and decorrelated simultaneously.

Hofmann, T. Probabilistic latent semantic analysis. – 1999.
Blei D. M., Ng A. Y., Jordan M. I. Latent dirichlet allocation. – 2003.
Vorontsov K. et al. Bigartm: Open source library for regularized multimodal topic modeling of large collections //AIST 2015.

Datasets

Dataset	D	W	T_{expected}	$T_{\min}$	$T_{\max}$
WikiRef220	220	4839	5	2	20
20NG	18846	2174	15–20	3	40
Reuters	10788	5074	90	5	150
Brown	500	7409	10–20	5	25
StackOverflow	895621	3430	40	5	60
PostNauka	3404	8417	15–30	5	50
ruwiki-good	8603	236018	10/90	5	100

D — number of documents, W — size of vocabulary, T — number of topics (expected T, and min/max values to be used in the experiments). Preprocessing: lemmatization, stop-words removal.

Results

Three features to summarize the behaviour of metrics:

- **Jaccard**: independence of the result from model random initialization (↓)
- **Informativity**: readability of obtained plots (↑)
- **Expected**: precision of the metric providing an expected number of topics (↑)

According to the results, *the number of topics is not a well-defined property of a particular corpus*.

	Score	Jaccard	Informativity	Expected
Information-theoretic	AIC	0.280	0.542	0.578
	AIC sparse	0.219	0.111	0.100
	BIC	0.128	0.444	0.461
	BIC sparse	0.274	0.164	0.128
	MDL	0.096	0.488	0.414
	MDL sparse	0.282	0.428	0.256
	renyi-0.5	0.470	0.507	0.425
	renyi-1	0.356	0.475	0.394
	renyi-2	0.230	0.299	0.183
Diversity	D-Spectral	0.456	0.144	0.083
	D-avg-L2	0.682	0.250	0.119
	D-cls-H	0.595	0.245	0.189
	D-avg-JH	0.302	0.053	0.022
Clustering	lift	0.383	0.123	0.033
	holdout-perplexity	0.228	0.025	0.019
	perplexity	0.218	0.023	0.014
	CHI	0.277	0.157	0.008
	SilhC	0.233	0.079	0.028
	average coherence	0.780	0.472	0.208
	uni-theta-divergence	0.470	0.197	0.047

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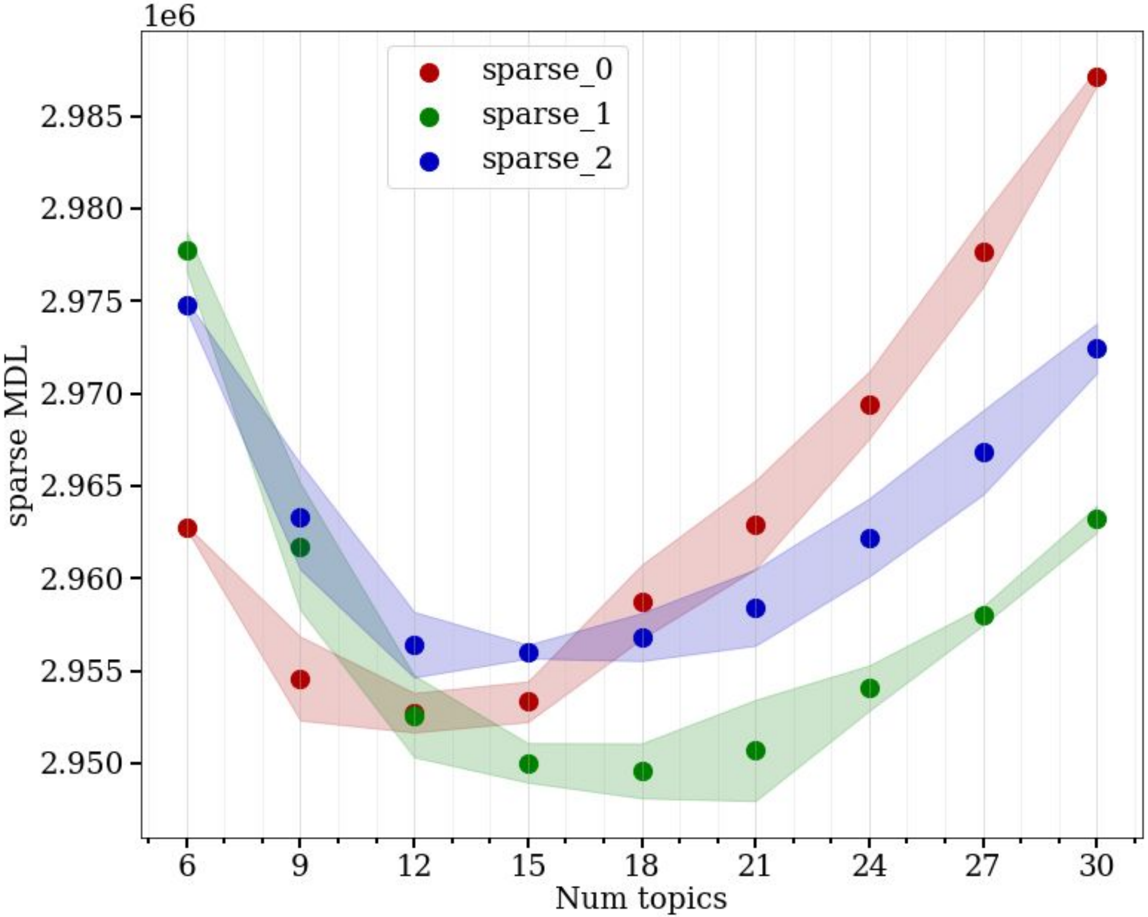
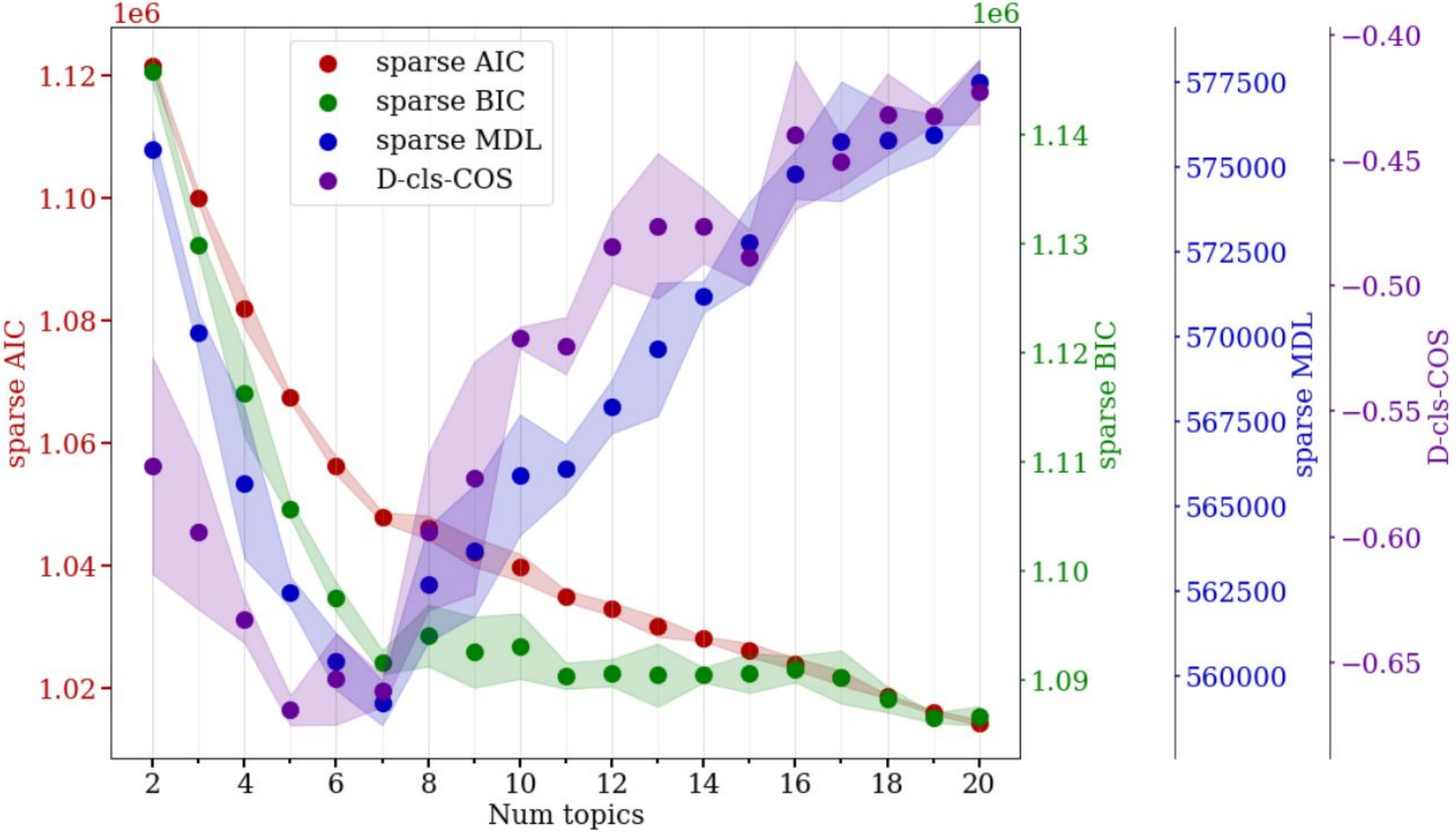
Results

- Optimal number of topics depends on the model.
- Randomness causes variance.



Sparse MDL criterion for models with different sparsity hyperparameter values (WikiRef220).

Results



Different criteria often do not agree with each other (but sometimes they do).
A set of quality metrics exploring various T for PLSA (WikiRef220). Cosine-based diversity is taken with a negative sign. All metrics agree with 7 being a reasonable value for T.

The work was first presented at [AIST 2023: The 11th International Conference on Analysis of Images, Social Networks and Texts](). 30 September, 2023

Conclusion

- Number of topics is a method- and a model-dependent quantity.
- Number of topics is not an absolute property of a particular corpus.
- Perplexity is not helpful for finding the number of topics.
- Simplest approaches (AIC, BIC, MDL; Rényi) achieve best results.

Recommendations (based on evidence):

- Examine several related measures.
- Information-theoretic methods (AIC, BIC, MDL) are better employed in conjunction.

Recommendations (based on reflections on the topic):

- Select a model according to a secondary task.
- Build a hierarchy of topics and prune it afterwards.
- Utilize the process of human (semi-) supervision.

The main purpose of topic modeling should be the search for such a method of model training which, given the number of topics, results in a model whose topics in the absence of external criterion are all interpretable.