WHAT DO WEBSITES SAY ABOUT FIRM-LEVEL INNOVATION? - A MACHINE LEARNING APPROACH

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MOTIVATION

Drawbacks of traditional firm-level innovation indicators that are based on large-scale questionnaire-based surveys:

- Lack of geographical coverage
- Costly
- It takes time to process the data
- Firm participation is required

➢ However, innovation indicators with information scraped from firm websites would allow an automatized, timely and comprehensive analysis of firm-level innovation activities.

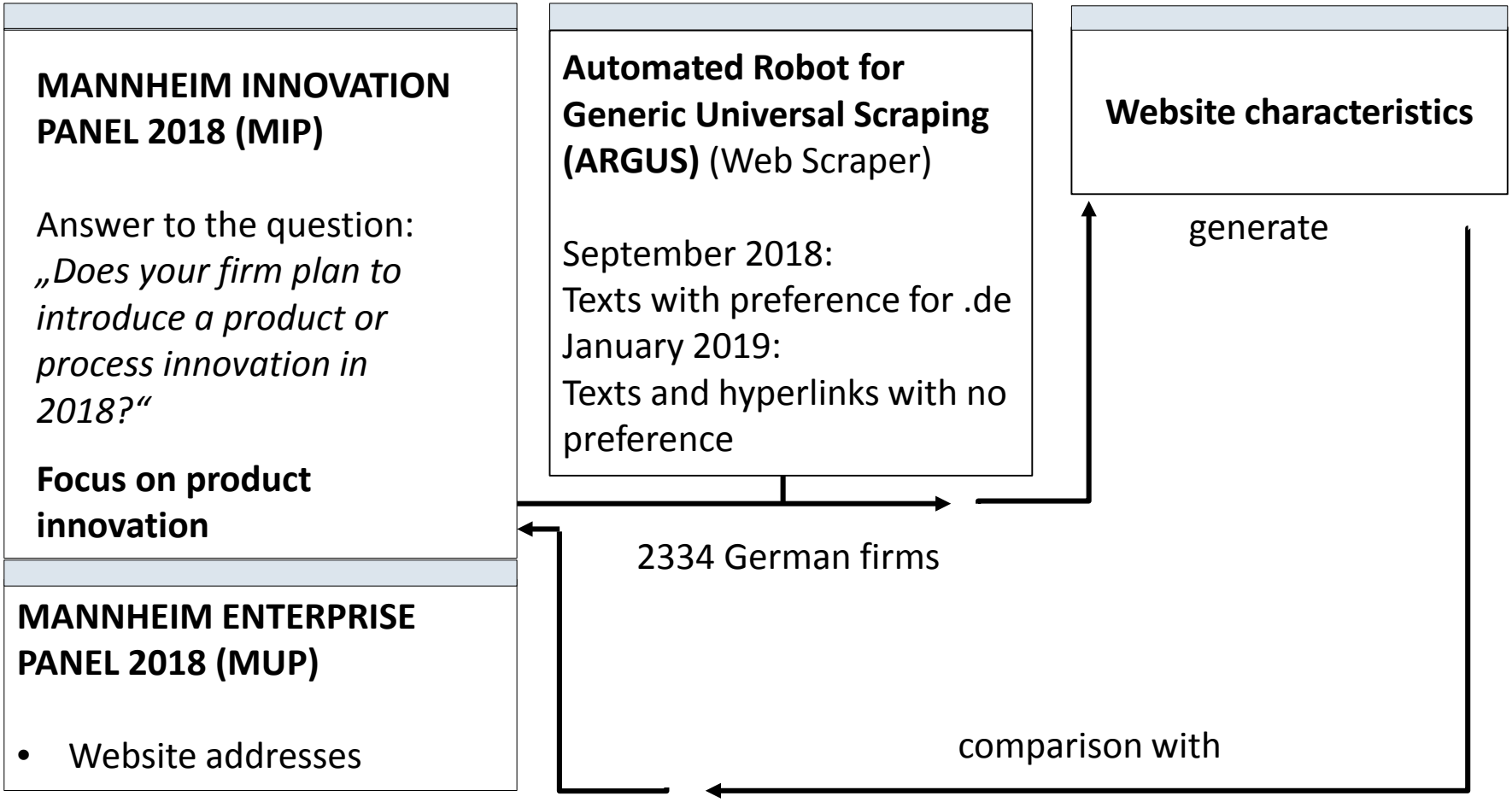
But do websites contain measurable information about firm-level innovation activities and which website characteristics best predict a firm‘s innovation status?

WEBSITE CHARACTERISTICS

Direct Information	Keywords	Innovation-related and/or product-related terms
		Terms related to emerging technologies (*from Wikipedia's list of emerging technologies)*
	Latent patterns	Topics generated by the latent Dirichlet allocation (LDA)

Indirect Information	Economic sector	Clusters based on website similarities (k-means algorithm)
	Firm size	Number of subpages; total amount of characters
	International orientation	Percentage of subpages in English language; number of occurrences of the word '*German*'
	Relationships to other firms	The sum of incoming and outgoing hyperlinks
	Social media	Hyperlinks to Facebook, Instagram, Twitter, YouTube, Kununu, LinkedIn, XING, GitHub, Flickr and Vimeo

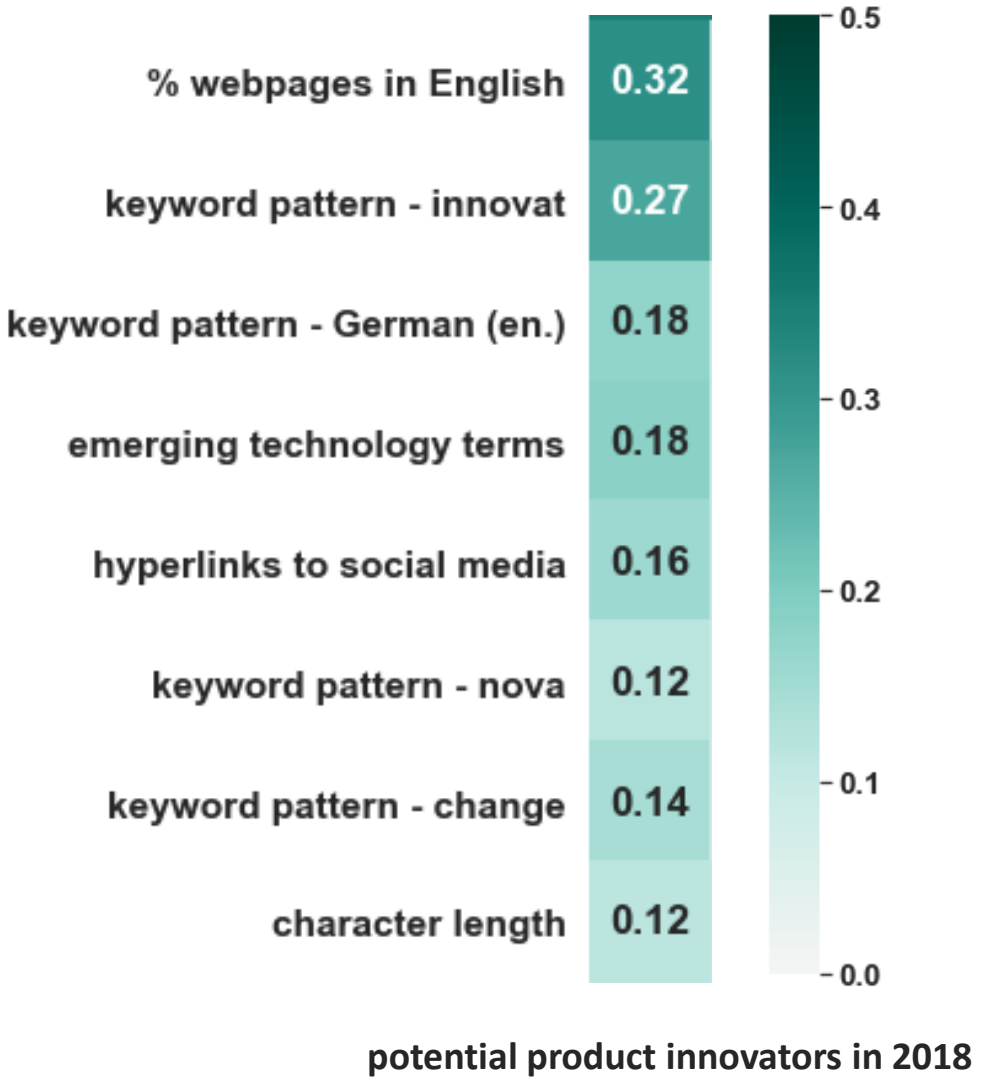
SUMMARY – RESEARCH APPROACH



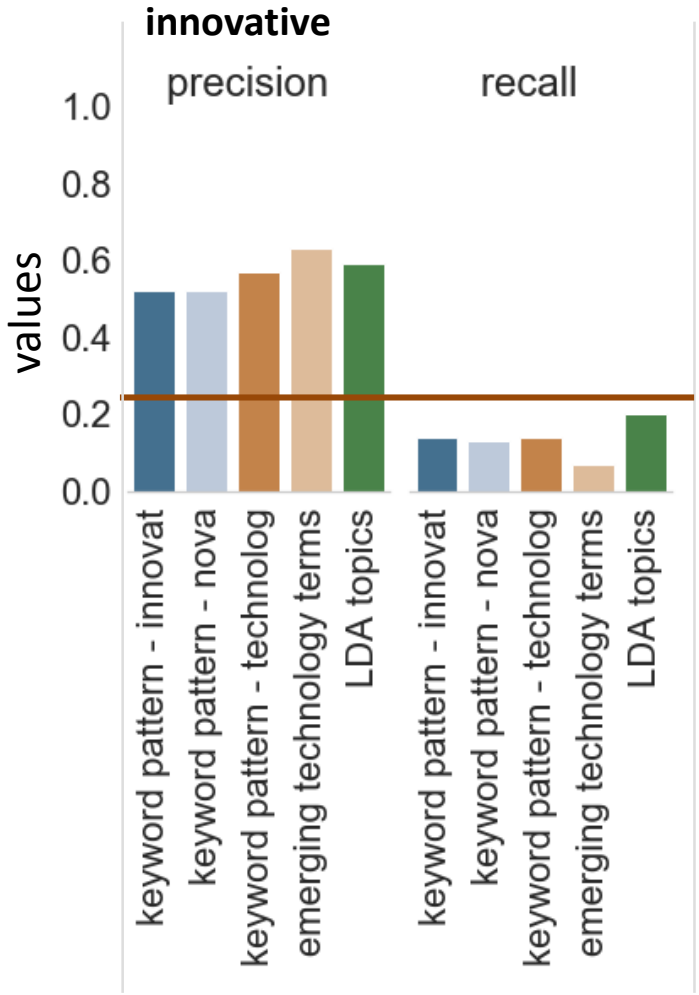
WEBSITE CHARACTERISTICS AND PRODUCT INNOVATION STATUS
Pearson correlation coefficients

The term *innovat* and the percentage of webpages in English language show the strongest correlation with potential product innovators in 2018.

The p-values of all correlation coefficients are <0.01.



PREDICTING THE PRODUCT INNOVATION STATUS WEBSITE CHARACTERISTICS CAPTURING DIRECT INFORMATION



- Logistic regression model with LASSO-regularization
- 10-fold cross-validation
- Cut-off point: 0.5
- Dependent variable: potential product innovators in 2018
- 24% of all firms planned to introduce a product innovation

— Random weighted guess

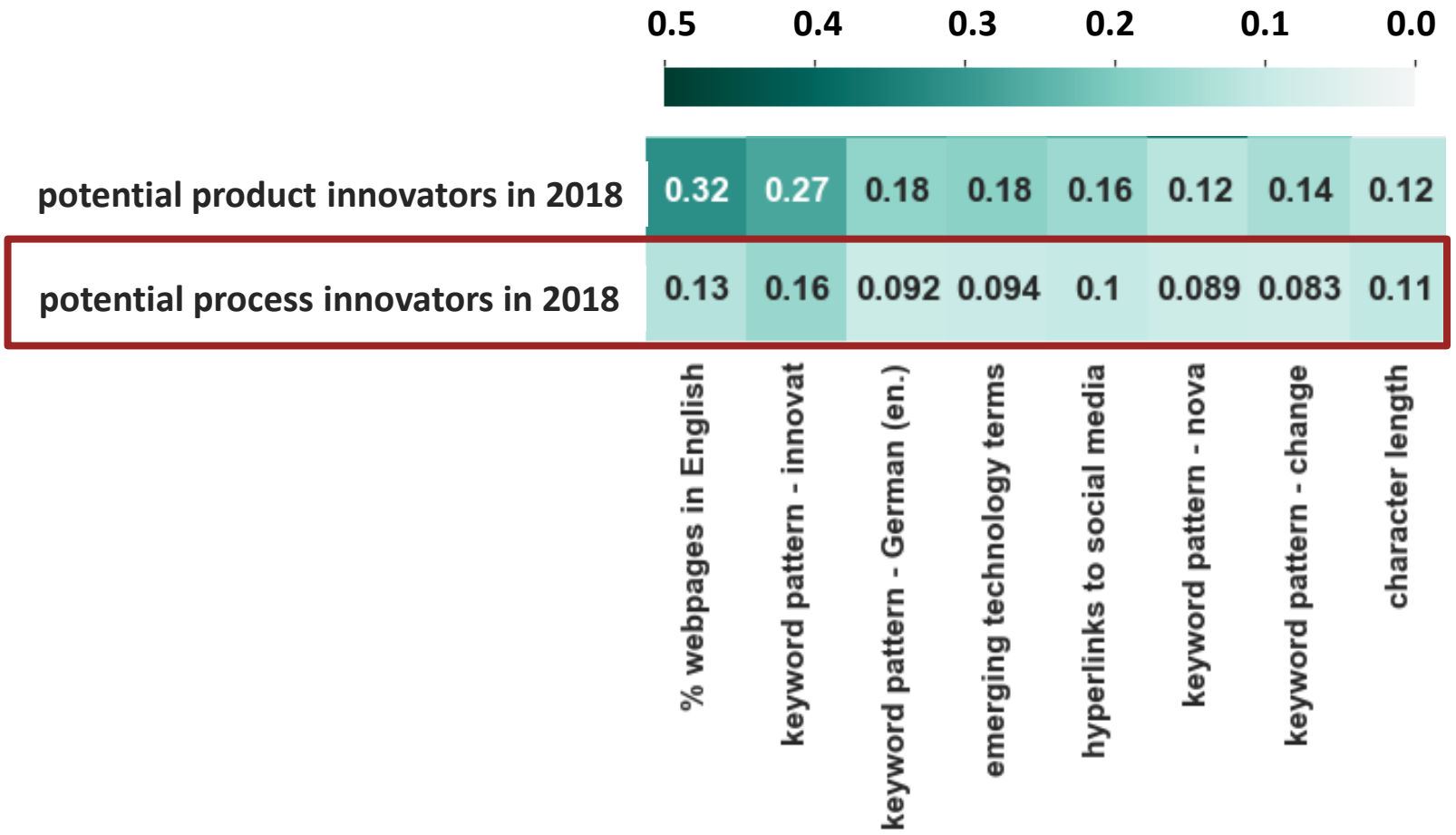
Results for website characteristics capturing *indirect information* are comparable

PREDICTING THE PRODUCT INNOVATION STATUS USING ALL IDENTIFIED WEBSITE CHARACTERISTICS COMBINED

Model	Innovative		Non-Innovative	
	Precision	Recall	Precision	Recall
random weighted guess	0.24	0.24	0.76	0.76
All website characteristics	0.62	**0.32**	0.82	0.94

- Logistic regression model with LASSO-regularization
- 10-fold Cross-validation
- Cut-off point: 0.5
- Dependent variable: potential product innovators in 2018
- Independent variables: number of occurrences of the keyword patterns nova, techno, innovat, German (en.), software, system, solution; emerging technology terms; combinations of the keyword patterns inno combined, inno count; LDA topics; number of subpages; total amount of characters; dummies indicating k-means clusters; % webpages in English language; sum of incoming and outgoing hyperlinks; hyperlinks to social media websites

WEBSITE CHARACTERISTICS AND POTENTIAL PROCESS INNOVATORS 2018
Pearson correlation coefficients



CONCLUSION

- Innovation-related keywords as well as the keyword `German‘, the share of English language, latent patterns and clusters based on website similarities, etc. are all related to firm-level product innovations.
- No single feature is able to detect a sufficient amount of innovative firms, but combinations of different website characteristics improve predictions and perform better than simple solutions.
- The innovation indicator “potential product innovators in 2018” provides downward-biased evaluation metric scores because some firms deviate and do innovate/not innovate.
- Moreover, website characteristics are more strongly related to product innovators than to process innovators.

Thank you for your attention!

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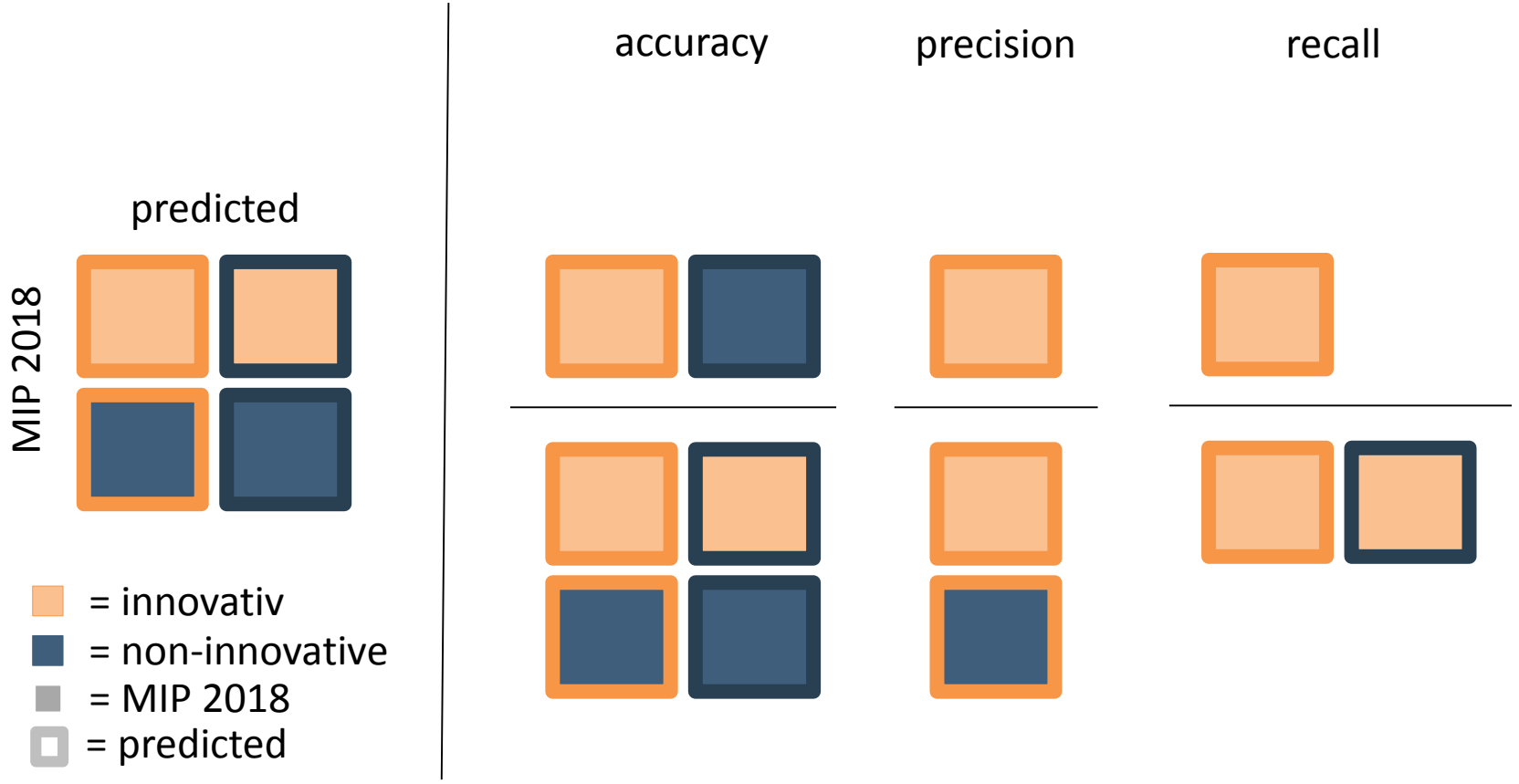
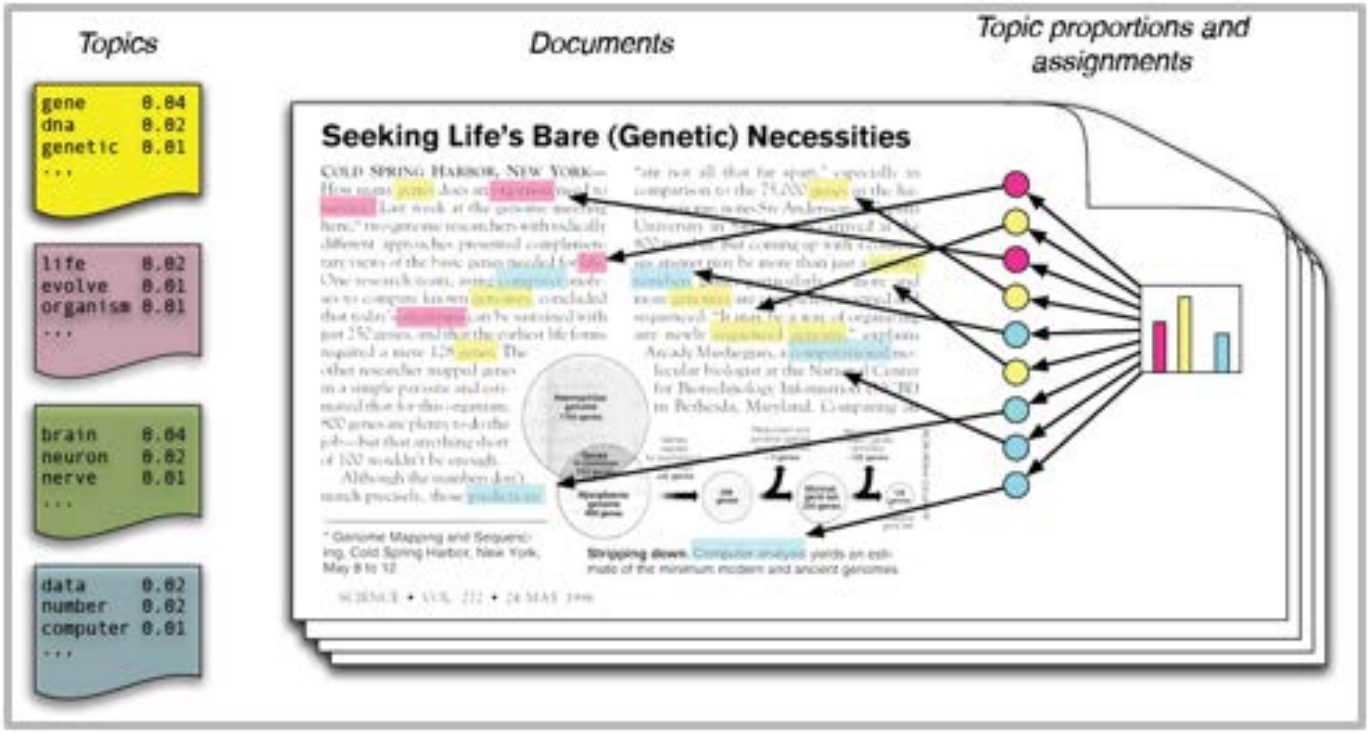
METRICS: ACCURACY, PRECISION AND RECALL



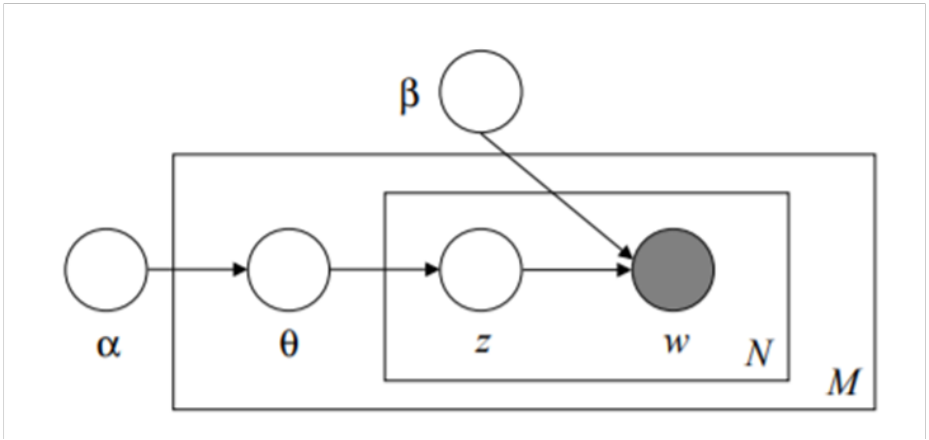
LDA – LATENT DIRICHLET ALLOCATION



Source: https://medium.com/@connectwithghosh/topic-modelling-with-latent-dirichlet-allocation-lda-in-pyspark-2cb3ebd5678e, accessed: 07.04.2019

LDA

$$p(D|\alpha,\beta) = \prod_{d=1}^{M} \int p(\theta_d|\alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn}|\theta_d) p(w_{dn}|z_{dn},\beta) \right) d\theta_d.$$

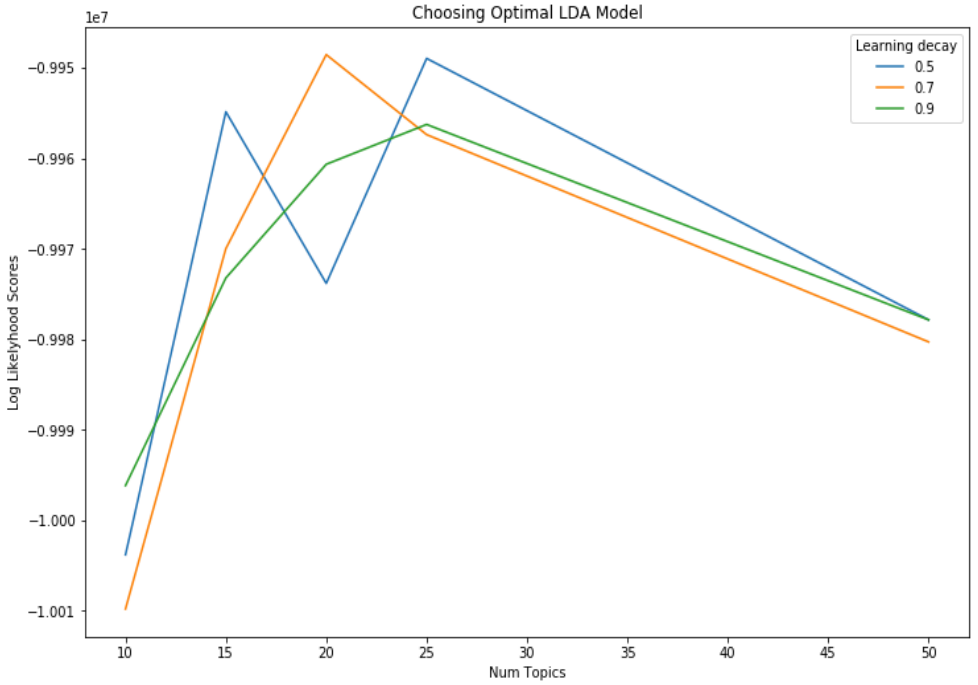


w:	word
D:	corpus
M:	collection of documents
N:	sum of words
n:	index word
d:	index document
θ	distribution of topics in document
z:	topic
α,β:	hyperparameters of Dirichlet allocation

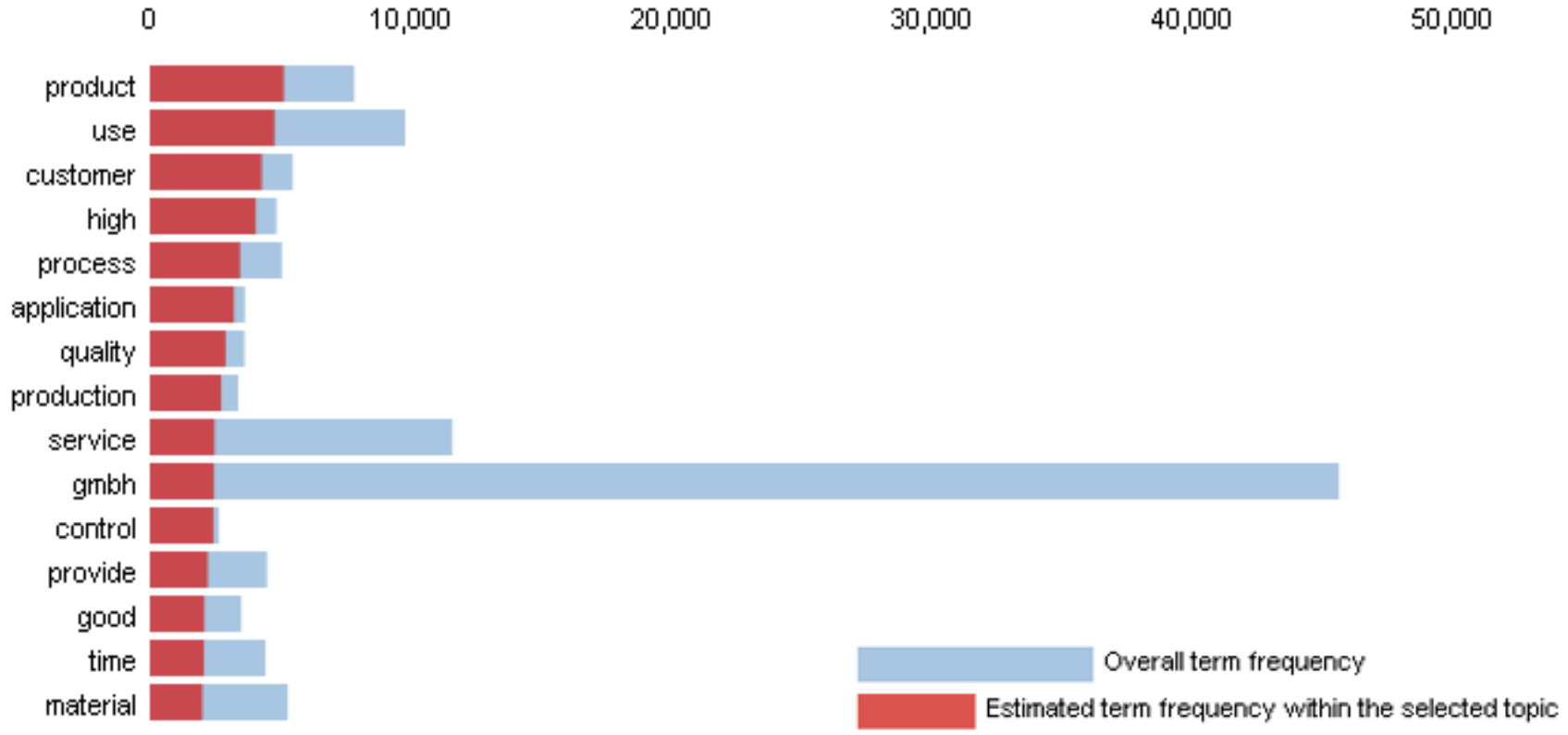
LDA

Preprocessing:

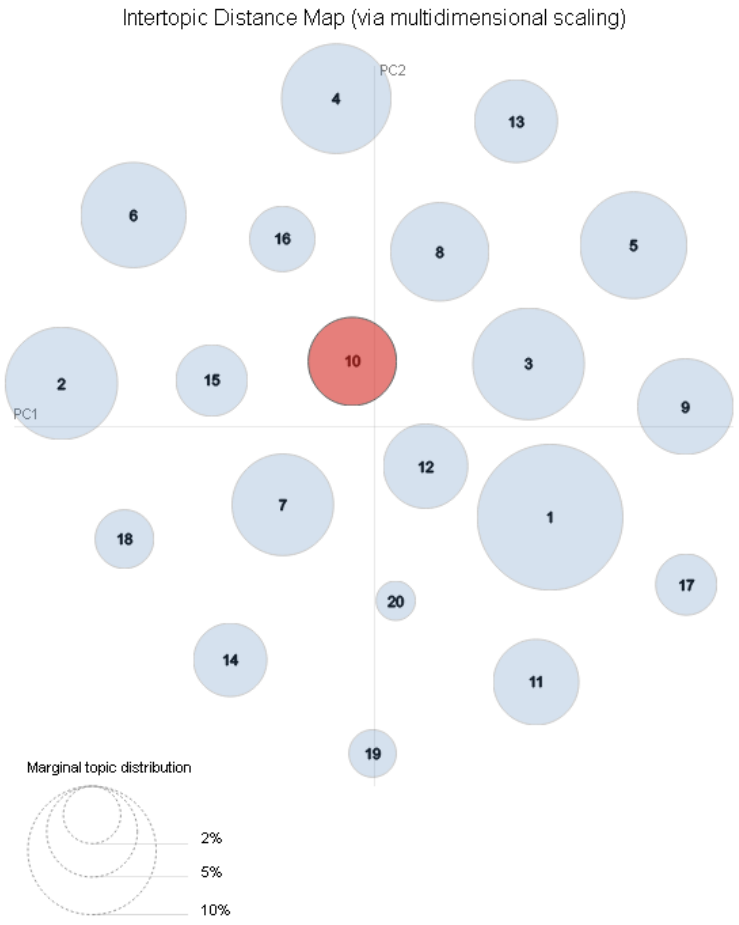
- Exclusion of all subpages mentioning in their URL terms like: *imprint, contact, location* or *general terms and conditions*
- Only words that appear at least 150 times are included
- Texts are lemmatized
- Optimal number of topics is chosen by means of a grid-search

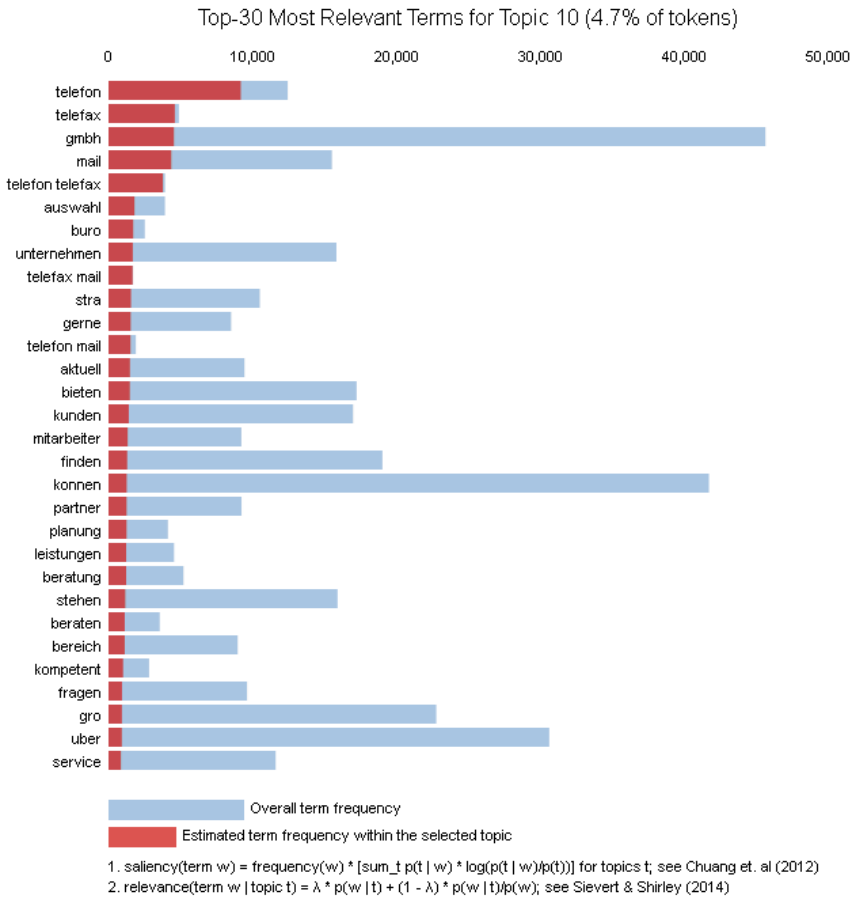


RESULTS: TOP 15 MOST SALIENT WORDS FOR THE TOPIC ‘PRODUCT DESCRIPTIONS IN ENGLISH LANGUAGE’ (EXAMPLE FOR A POSITIVELY-CORRELATED LDA TOPIC WITH POTENTIAL PRODUCT INNOVATORS IN 2018).

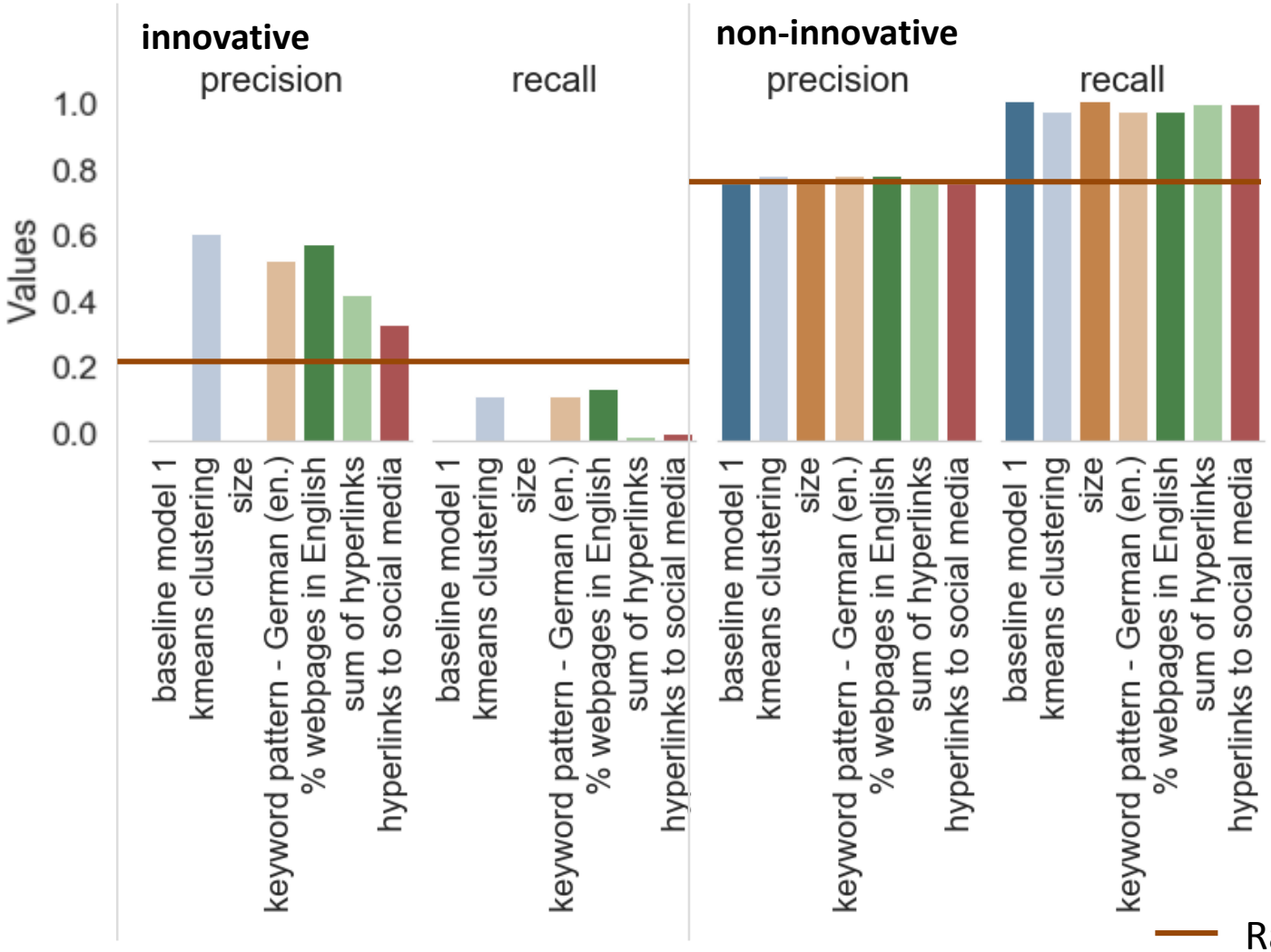


LDA – TOPIC 10 – NEGATIVE CORRELATION



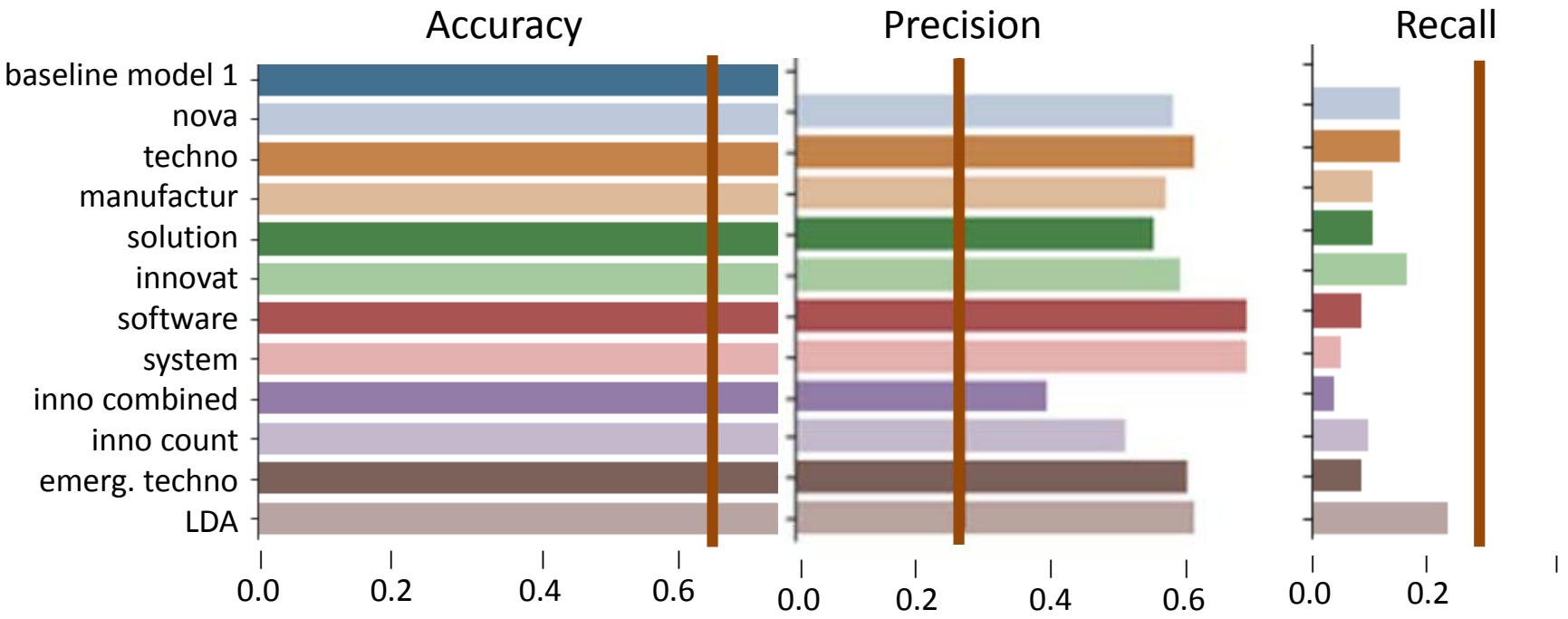


PREDICTING THE INNOVATION STATUS
WEBSITE CHARACTERISTICS - INDIRECT INFORMATION



- Logistic regression model with LASSO-regularization
- 10-fold cross-validation
- Cut-off point: 0.5
- Dependent variable: potential product innovators in 2018

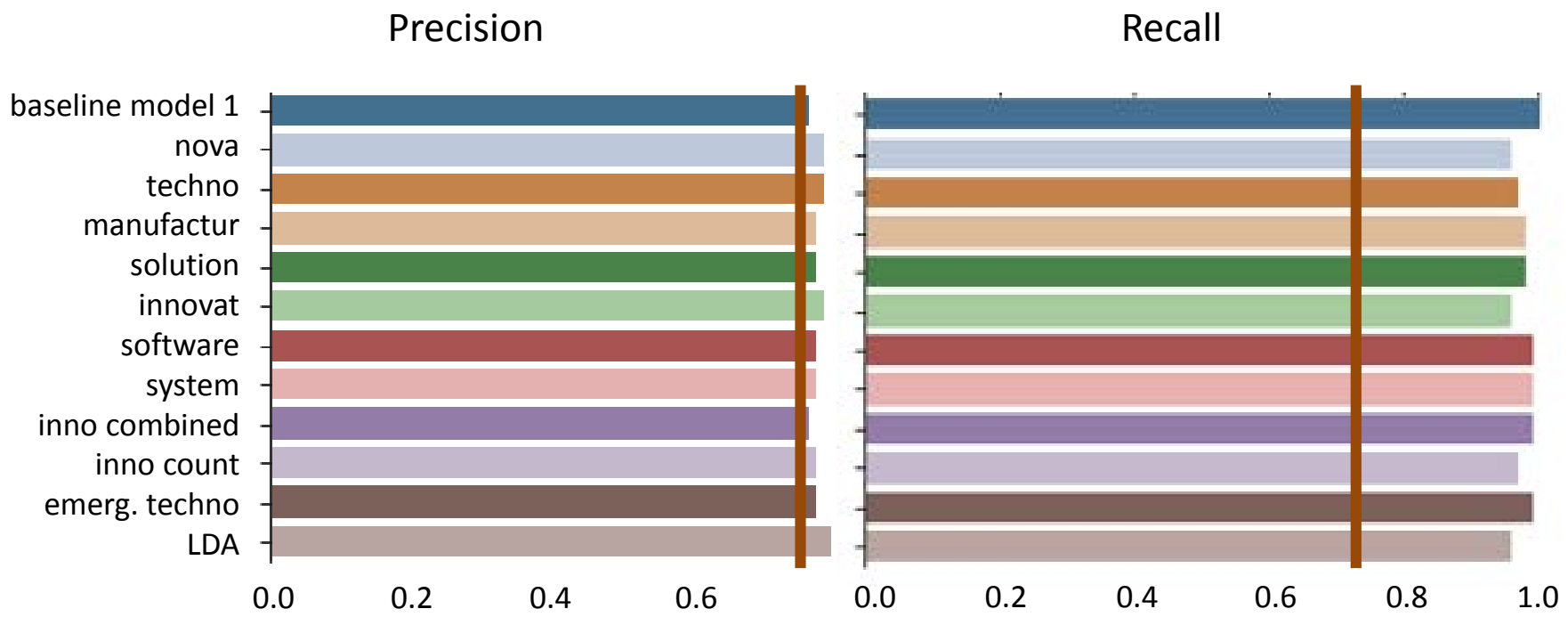
PREDICTING THE INNOVATION STATUS
WEBSITE CHARACTERISTICS - DIRECT INFORMATION
Innovative firms



Logistic regression model with LASSO-regularization
10-fold cross-validation
Cut-off point: 0.5
Dependent variable: potential product innovators in 2018

Random weighted guess

PREDICTING THE INNOVATION STATUS
WEBSITE CHARACTERISTICS - DIRECT INFORMATION
Non-innovative firms



Logistic regression model with LASSO-regularization
10-fold cross-validation
Cut-off point: 0.5
Dependent variable: potential product innovators in 2018

Random weighted guess

PREDICTING THE INNOVATION STATUS
POTENTIAL PROCESS INNOVATION IN 2018

Modell	Innovativ		Non-Innovativ	
	Precision	Recall	Precision	Recall
All website characteristics	0.75	0.06	0.80	0.99

Logistic regression model with LASSO-regularization
Cut-off point: 0.5
Dependent variable: potential process innovators in 2018
N=2334, mean of dependent variable: 0.23