PREDICTING INNOVATIVE FIRMS USING WEB MINING AND DEEP LEARNING

Jan Kinne & David Lenz May 2019

IGL 2019



MOTIVATION: SHORTCOMINGS OF TRADITIONAL INNOVATION INDICATORS

- Timeliness
- Coverage
- Data collection costs
- Granularity

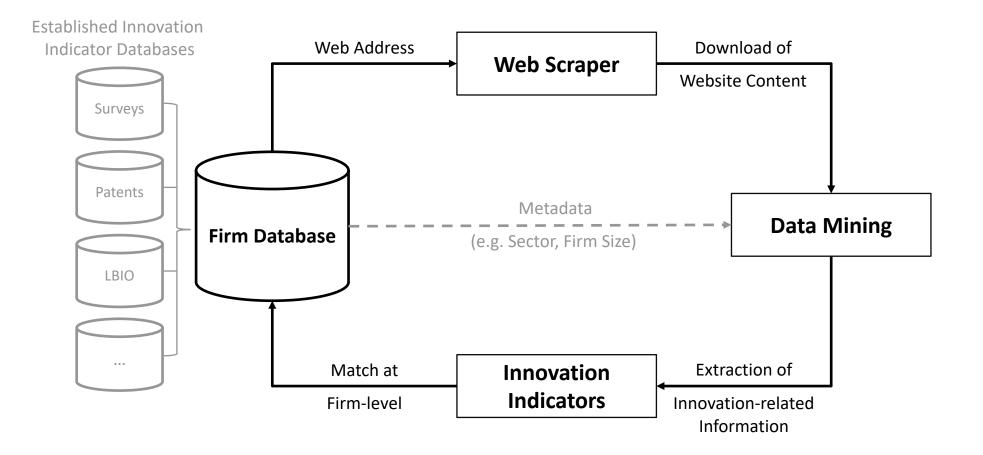
STI policy making requires an accurate and timely picture of the current state of the STI system in order to plan and evaluate policy measures in an evidence-based manner.

MOTIVATION: WEB MINING OF FIRM WEBSITES

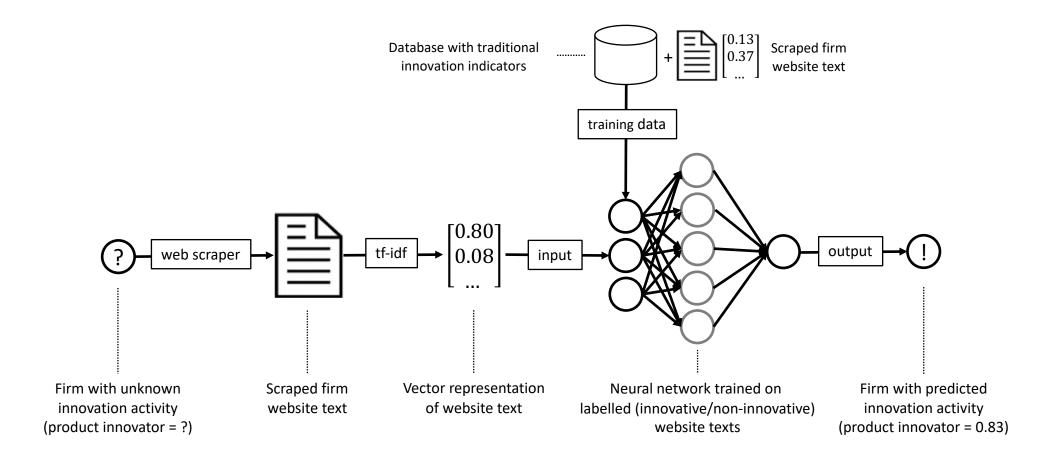
- Firms want us (as customers) to know how innovative they are.
- Almost all (significant) firms have websites nowadays.
- Important medium to tender and promote services and products.
- Firms have an incentive to keep their websites up-to-date.
- Firm website content is often related to product, service, and organisational innovations.

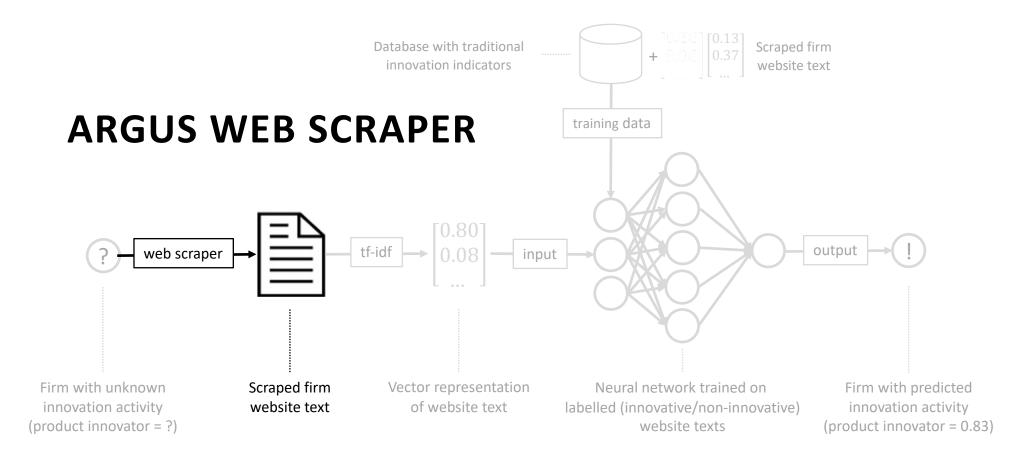
Using this openly accessible data to create timely and granular firm-level innovation indicators.

WEB MINING OF FIRM WEBSITES: ANALYSIS FRAMEWORK



DEEP LEARNING OF WEBSITE TEXT: FRAMEWORK

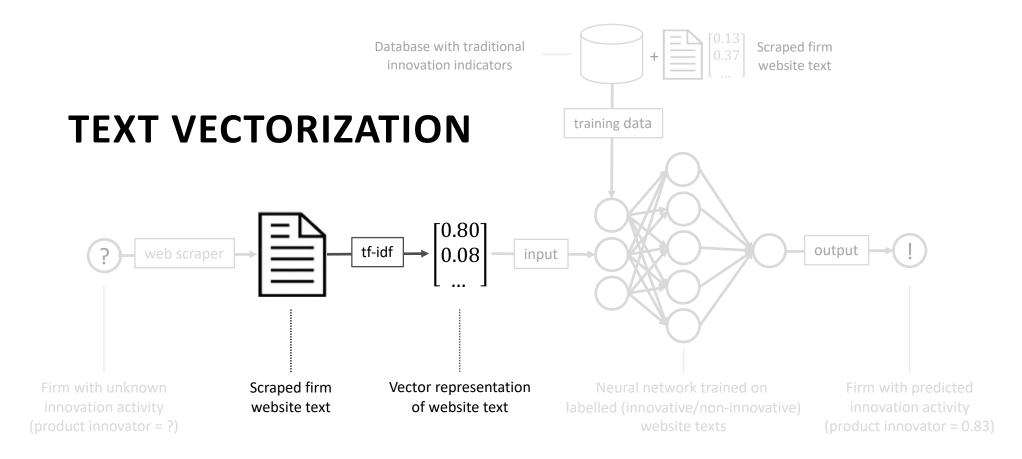




ARGUS WEB SCRAPER: OVERVIEW

- Free and easy-to-use web scraping tool with GUI [github.com/datawizard1337/ARGUS]
- ~1,000 webpages per minute per CPU core
- ~5 days for 50m webpages on an office-grade PC
- Scraping of hyperlinks and texts

G ARGUS		-	-1		×	
File Settings		Web Scraper Settings				
Browse for URL list						
Browse		Parallel Processes:		Select		
Delimiter:	Select -	Spider Type:		Select	_	
Encoding:	Select -	Scrape Limit:	1		-	
Load Columns		Prefer Short URLs:		Select	-	
ID Column:	Select -	Preferred Language:		Select		
URL Column:	Select -	Logging Level:		INFO	-	
Start Scraping						
Functions						
Stop Scraping		Postprocessing				
Terminate Job		Aggregate Webpage Texts				

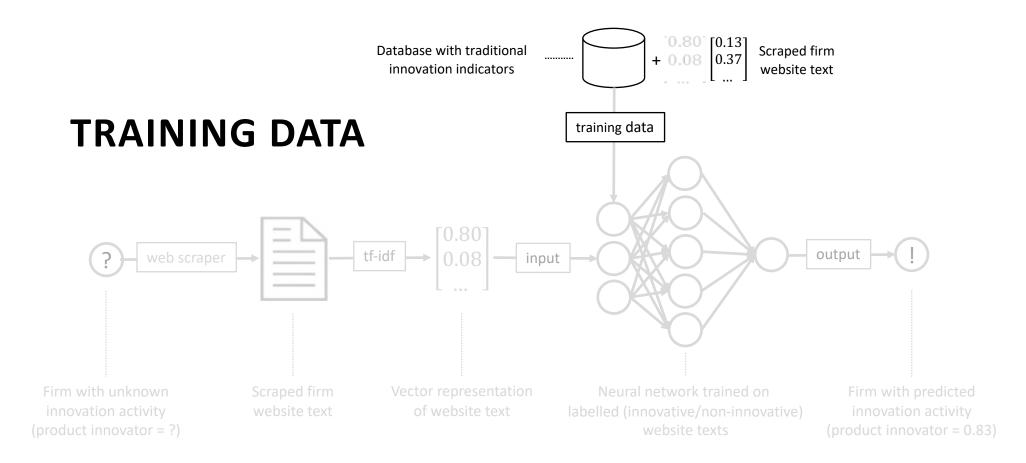


TEXT VECTORIZATION: WORKFLOW

- **Web scraping of 650,000 firm websites with max. 25 webpages each**
- 50 GB of raw text data
- Deep learning based filtering of "bloat" webpages (e.g. imprints)
- Aggregating webpages to the website level
- **Keeping max. 5,000 words per website**
- TF-IDF vectorization with popularity-based filtering (dictionary of ~6,150 words)

650,000 fixed size (6,150) vectors

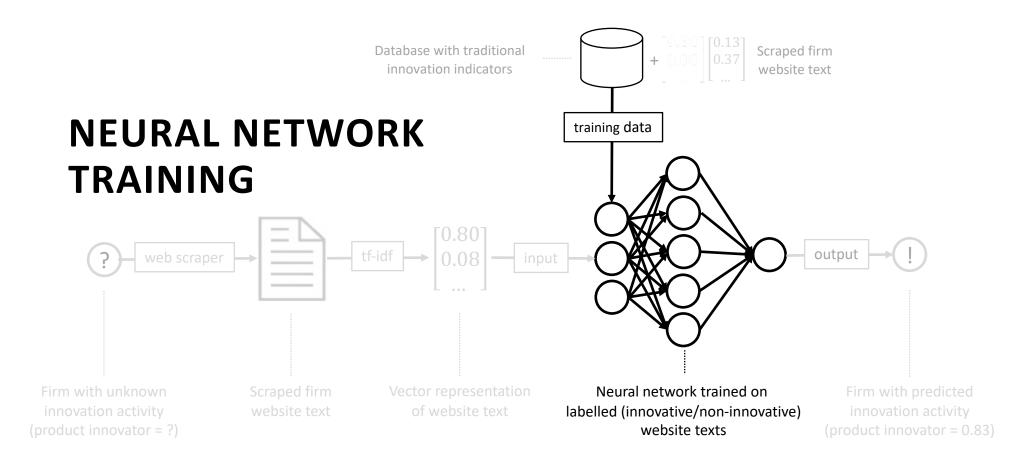
= 650,000 website texts of firms with unknown innovation status



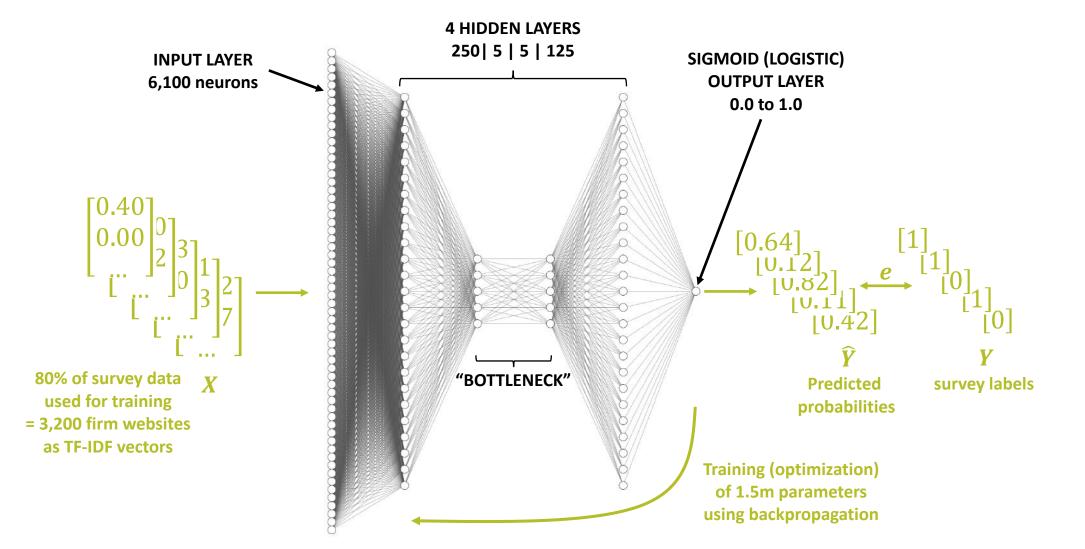
TRAINING DATA: MIP SURVEY DATA

- 2017 Mannheim Innovation Panel (MIP) traditional questionnairebased survey of ~4,000 firms in Germany
- Binary target variable: Firm was product innovator (YES | NO)

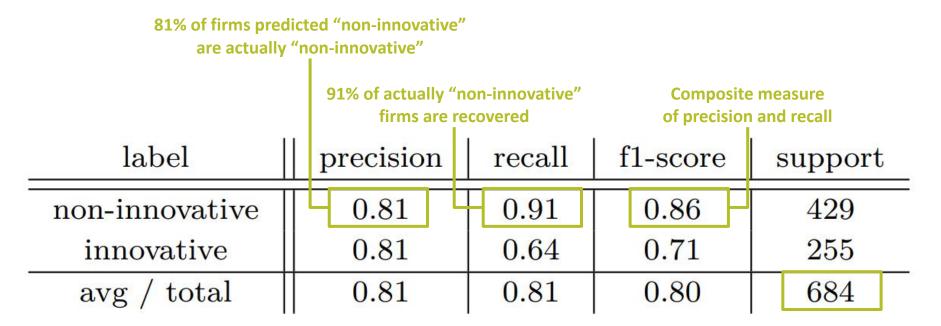
2 Product Innovation		
Product innovation describes a product (incl. services) whose components or a ware, applications, user friendliness, availability) are either new or significantly in		ted soft-
The innovation must be new to your enterprise, but it does not need to be new prise's evaluation of it. It does not matter if the innovation was developed by y aesthetic modifications of products (e.g. colouring, styling) are not regarded as proped and produced entirely by other enterprises, also does not count as product ir	to your sector or market. The sole significant factor is you your enterprise alone or in collaboration with other enterprise product innovations. Selling alone of innovations that have been selected as a sector of the sector	s. Purely
→ For examples of product innovation	ons, see the foldout section	
2.1 During the years 2014 to 2016, did your enterprise introduce ne	ew or significantly improved products / services?	
Yes	No \square_2 \rightarrow Please continue with Section	3.
• Web scraping of website texts \rightarrow TF	-IDF vectorization	
$\begin{bmatrix} 0.40 \\ 0.00 \\ 2 \end{bmatrix}_{2}^{0} \begin{bmatrix} 3 \\ 0 \end{bmatrix}_{2}^{1} \begin{bmatrix} 4,000 \text{ fixed size (6,150) vec} \\ 0 \end{bmatrix}_{2}^{1} \begin{bmatrix} 1 \\ 2 \end{bmatrix}_{2}^{1} \end{bmatrix}_{2}^{1}$	ctors $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ 4,0 $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ produ	00 labels: ct innovato
$X \begin{bmatrix} 1 & 3 \\ 1 & 3 \end{bmatrix} = \begin{bmatrix} 2 \\ 7 \end{bmatrix}$	$Y \begin{bmatrix} I \\ L \end{bmatrix} $	es no
[= 4,000 website texts o	of firms with known innovation	n status



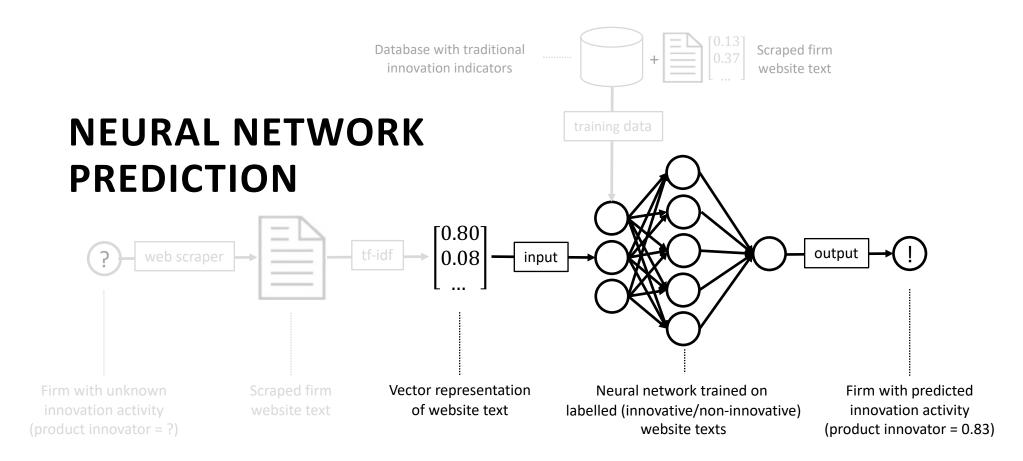
NEURAL NETWORK TRAINING: UNDERCOMPLETE AUTOENCODER-LIKE ARCHITECTURE



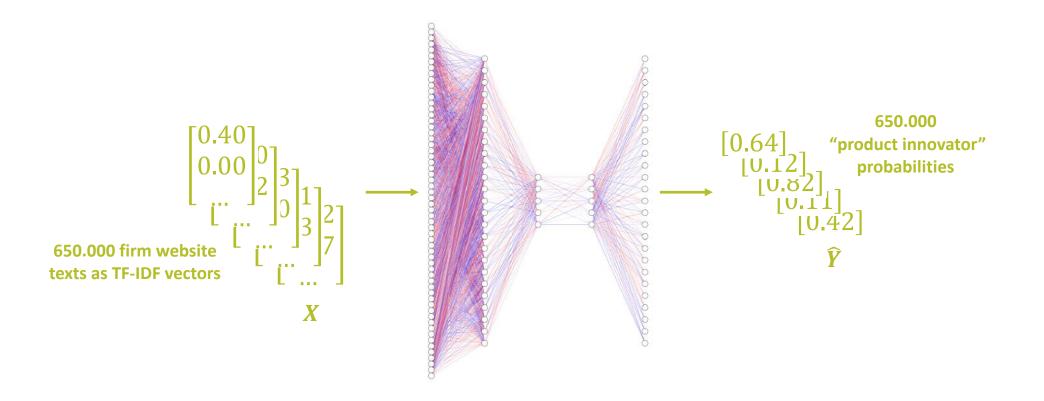
NEURAL NETWORK TRAINING: PREDICTION PERFORMANCE



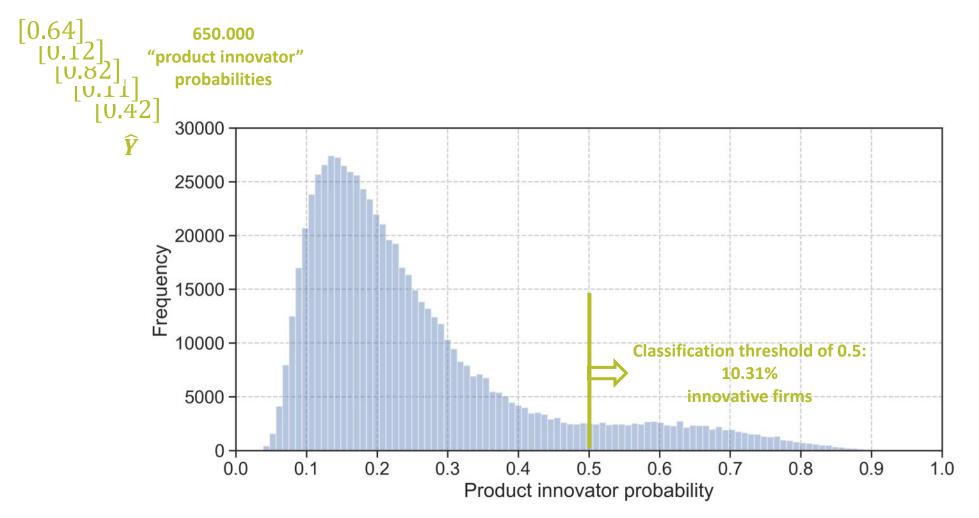
20% of survey data as test set



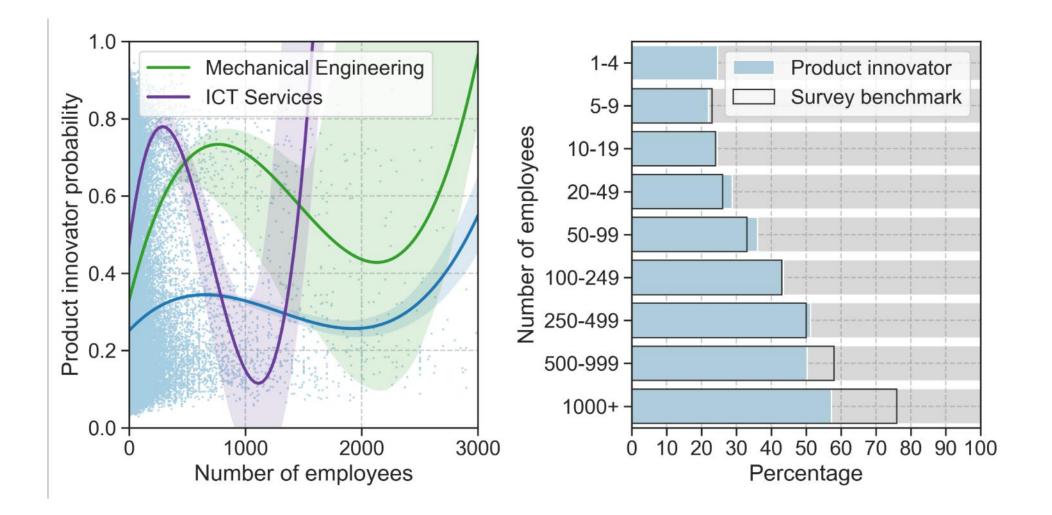
NEURAL NETWORK PREDICTIONS: OUT-OF-SAMPLE INNOVATION PREDICTION



NEURAL NETWORK PREDICTIONS: A CONTINUOUS INNOVATION INDICATOR

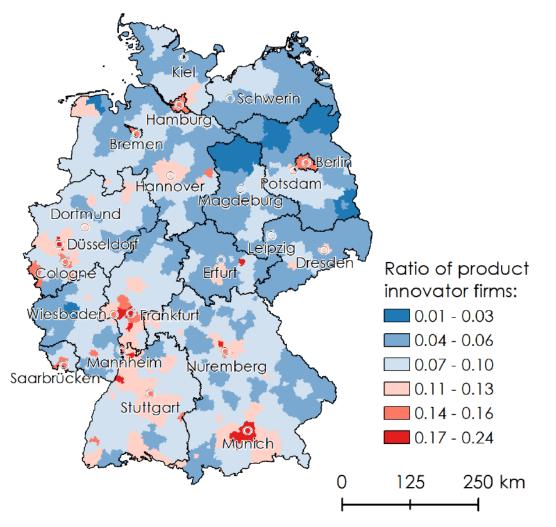


NEURAL NETWORK PREDICTIONS: INNOVATIVENESS BY FIRM SIZE

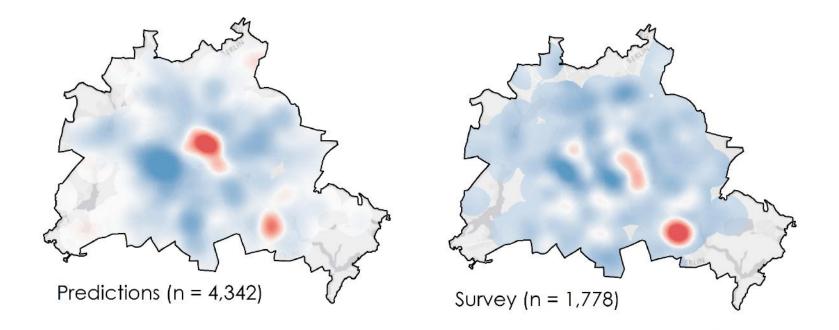


NEURAL NETWORK PREDICTIONS: INNOVATIVE DISTRICTS

- Higher shares of product innovators in urban areas
 - Correlation with population density: 0.61
- Lower shares of product innovators in East and North

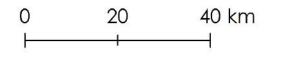


NEURAL NETWORK PREDICTIONS: MICROGEOGRAPHIC PATTERN



Dominant type of firm:

Non-innovative



FUTURE DIRECTIONS: SUPPORTING BIG DATA BASED POLICY MAKING

Industry-specific prediction models

ZEW

- Developing further web-based innovation indicators
- Formalization and dissemination of a coherent methodology
- Building up a panel database of web data
- Application in policy evaluation projects
- Investigating microgeographic diffusion of innovation and technology

THANKS!







zew.de/en/team/jki

github.com/datawizard1337

twitter.com/jan_kinne