Essays on the Application of

Statistical Learning

in

Empirical Economic Research

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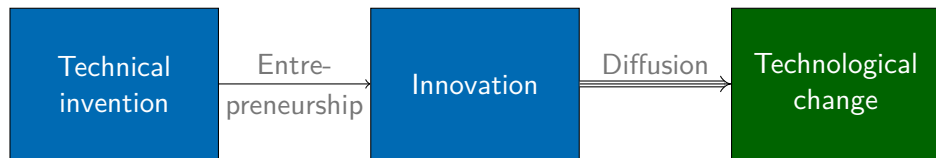
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Outline of talk

Mapping Technologies to Business Models: An Application to Clean Technologies and Entrepreneurship

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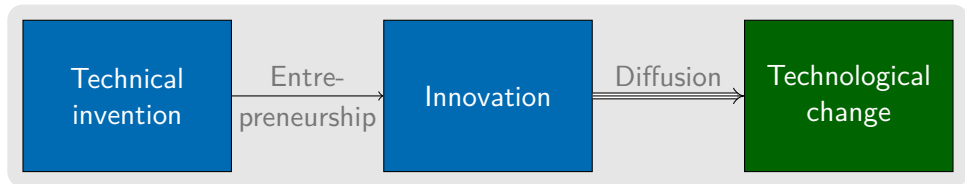# Technological innovation and its measurement

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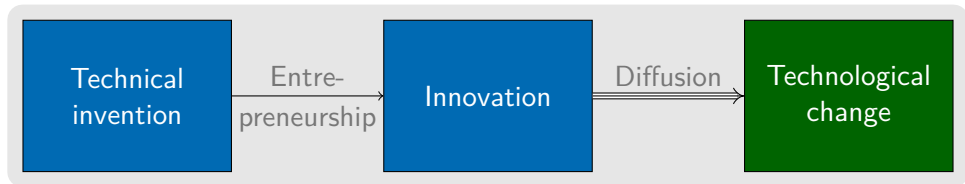
Patents *have become a surrogate for measuring the innovation process.*

Jaffe (2021)

Technological innovation and its measurement

Patents *have become a surrogate for measuring the innovation process.*

Jaffe (2021)

Patent *subclasses provide a [. . .] reliable picture of a firm's technological capabilities.*

Aharonson et al. (2016)

Patents and start-ups

A measurement problem

Start-ups barely file patents (Graham et al., 2008; Helmers et al., 2011):

- distracting engineers/managers from key functions (Mann, 2005)
- costs of patenting/patent litigation too high (Graham et al., 2009)
- disclosure through patent allows 'design around' (Mann, 2005)
- patents impact VC decisions as property rights, not as signals of technology quality (Hoenig et al., 2015)

Research question I

How to capture the role of start-ups in the innovation process?
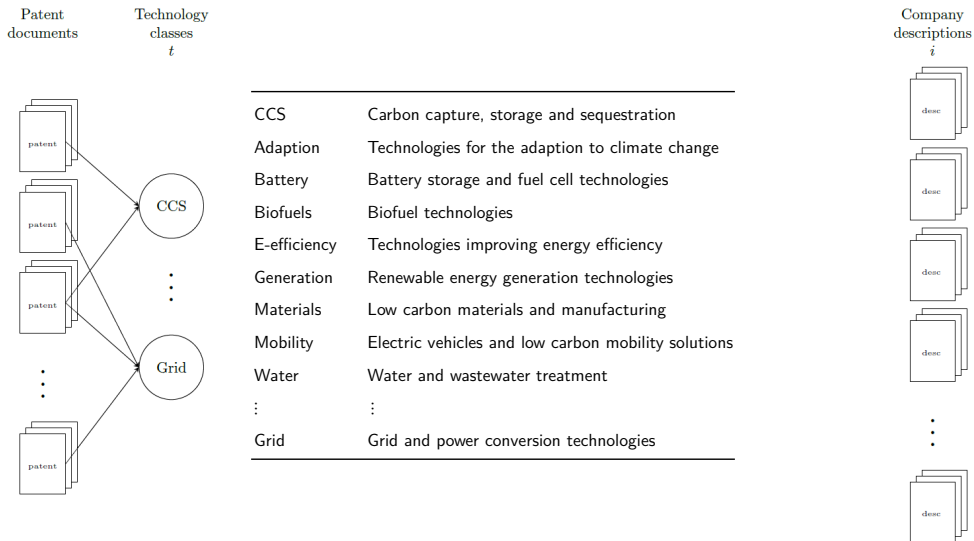
Textual innovation data

Legal obligation to publish business purpose at business registration
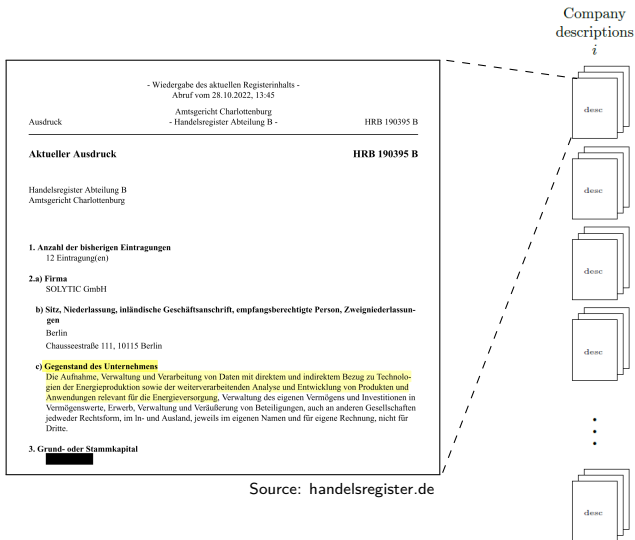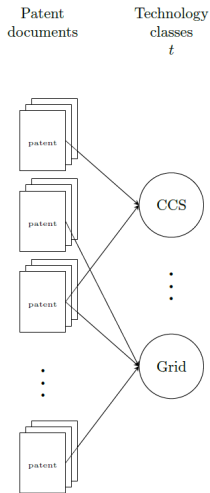

Source: handelsregister.de

Textual innovation data
Patent texts and assigned technology classes

| Patent documents | Technology classes t | | | Company descriptions i |

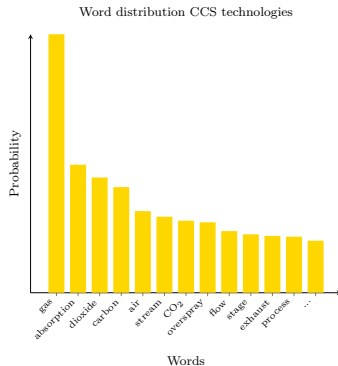| CCS | Carbon capture, storage and sequestration |
Adaption	Technologies for the adaption to climate change
Battery	Battery storage and fuel cell technologies
Biofuels	Biofuel technologies
E-efficiency	Technologies improving energy efficiency
Generation	Renewable energy generation technologies
Materials	Low carbon materials and manufacturing
Mobility	Electric vehicles and low carbon mobility solutions
Water	Water and wastewater treatment
⋮	⋮
Grid	Grid and power conversion technologies

From patents to technology descriptions

L-LDA (Ramage et al., 2009)

Goal: Derive technology-word distributions from expert-labeled corpus of patent docs

Contextualized vector representations

BERT (Devlin et al., 2018)

Goal: Derive contextualized vector representations of technology & business descriptions

$$X_{CCS}_{(1 \times Q)} = \langle \text{gas, absorption, dioxide}, \dots, \text{scrub}, \dots \rangle$$

SBERT $\downarrow$

$$X_{CCS}_{(1 \times 384 \, \forall Q)} = [0.006, 0.277, 0.288, \dots 0.590]'$$
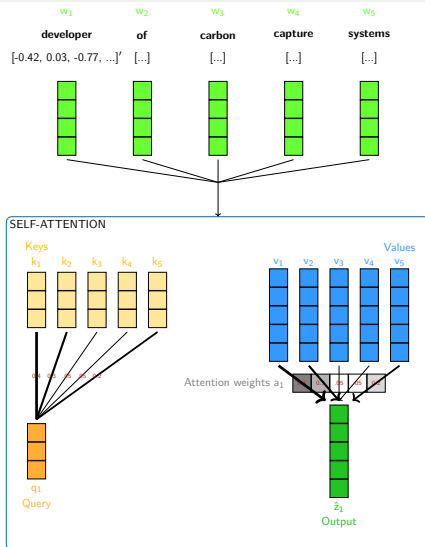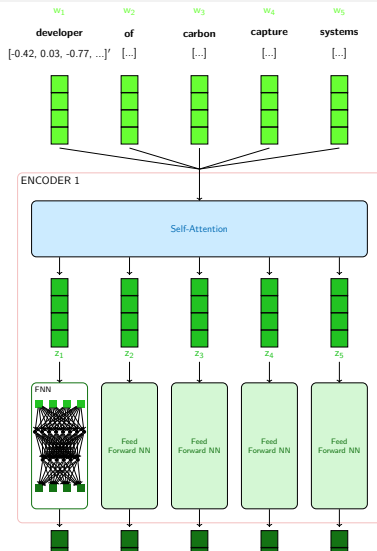
Excursus: BERT

Model architecture
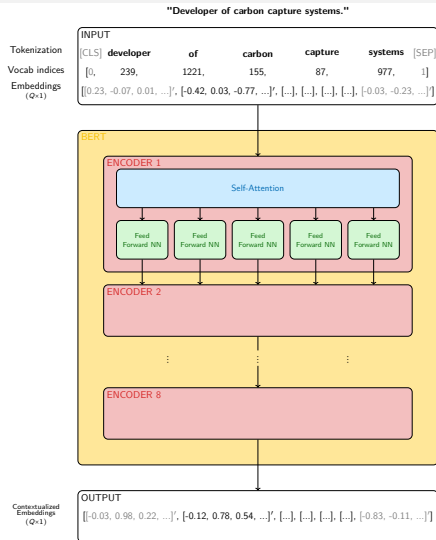
Attention Is All You Need (Vaswani et al., 2017)

Let tokens 'look around' the whole input, and decide how to update its representation based on on what it sees
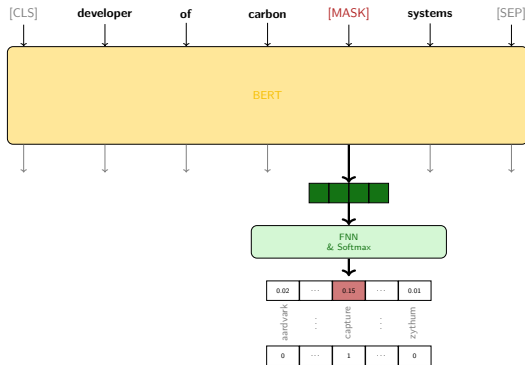
Encoder

After Attention, each token pondering for itself about what it has observed previously
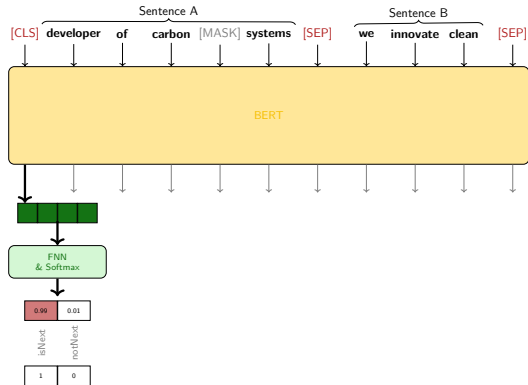
Training BERT
Self-supervised learning based on English Wikipedia

1. Masked language modeling

| [CLS] | developer | of | carbon | [MASK] | systems | [SEP] |

BERT

FNN
& Softmax

| 0.02 | ⋯ | 0.15 | ⋯ | 0.01 |

aardvark ⋮ capture ⋮ zythum

| 0 | ⋯ | 1 | ⋯ | 0 |

2. Next sentence prediction

Sentence A
Sentence B

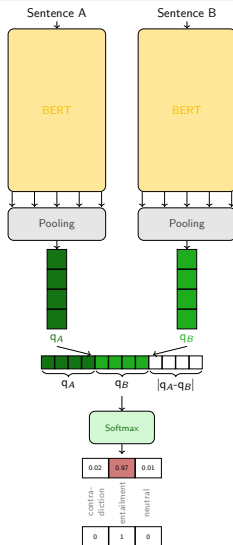| [CLS] | developer | of | carbon | [MASK] | systems | [SEP] | we | innovate | clean | [SEP] |

BERT

FNN
& Softmax

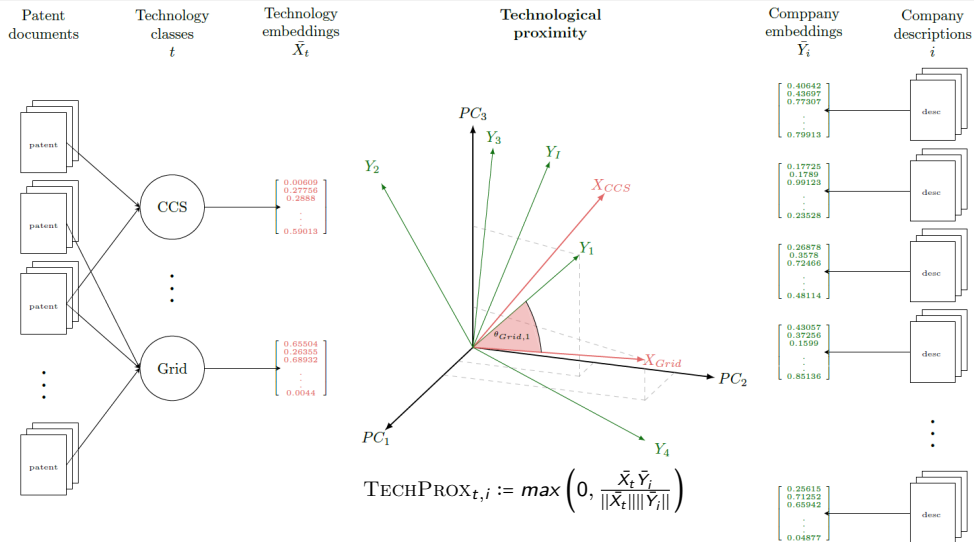| 0.99 | 0.01 |

isNext notNext

| 1 | 0 |

Finetuning BERT: SBERT (Reimers et al., 2019)

Finetuning based on collection of sentence pairs labeled for entailment, contradiction, and semantic independence

Mapping framework

Cosine similarity as measure of a company's technological orientation

$$\text{TECHPROX}_{t,i} := max\left(0, \frac{\bar{X}_t \bar{Y}_i}{||\bar{X}_t||||\bar{Y}_i||}\right)$$

Application

Fight against climate change requires new technological pathways and radical innovations (*inter alia* European Commission (2019), United Nations (2015))

- ▸ but: technological path dependencies and system/innovation inertia among incumbents (Aghion et al., 2016; Patel et al., 1997)
- ▸ costly: delay in redirecting innovation towards clean technologies (Benner, 2009; Dijk et al., 2016; Sick et al., 2016)
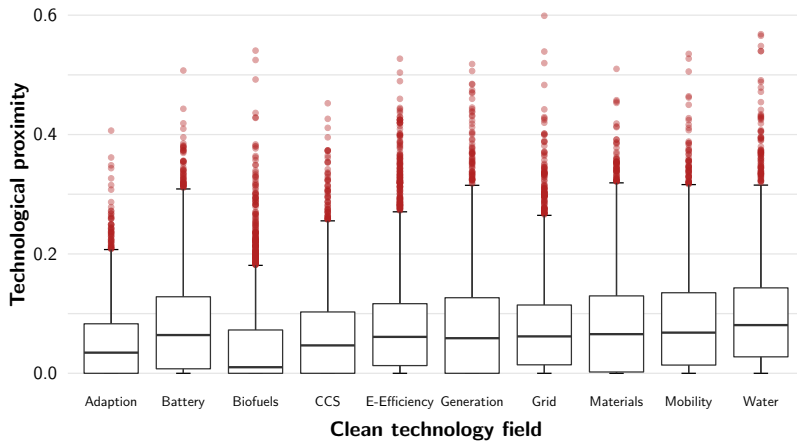- ⇒ special role of new (path-independent!) ventures in driving clean technology change

Research question II

Which role do start-ups play in the technological transition to higher levels of decarbonization?

Application

Application
A glance at the 'outliers'

The development, production and sale of ecological plant strengtheners and ecological plant protection.

Application
A glance at the 'outliers'

Development and production of energy systems, in particular in connection with fuel cells.

Development, manufacture and marketing of systems for the production of synthetic fuels and in particular systems for the production of synthetic fuels from carbon dioxide.

Application
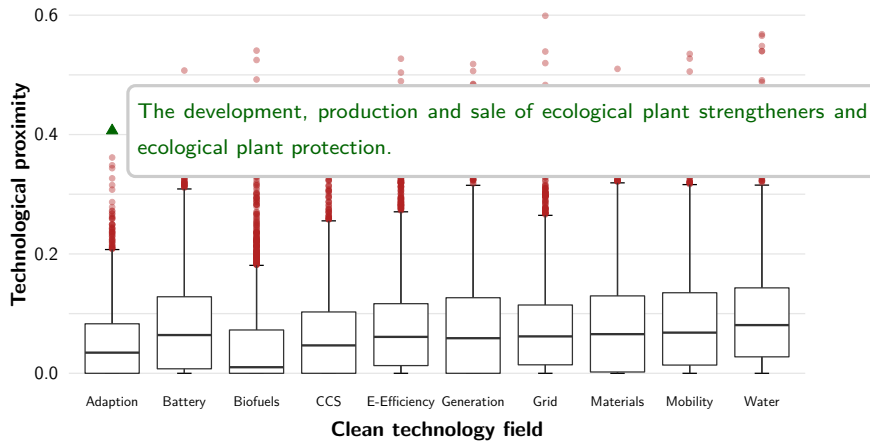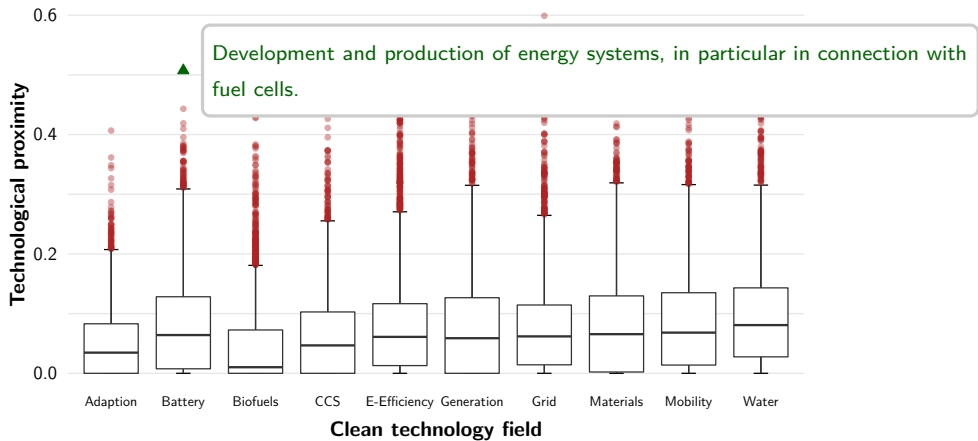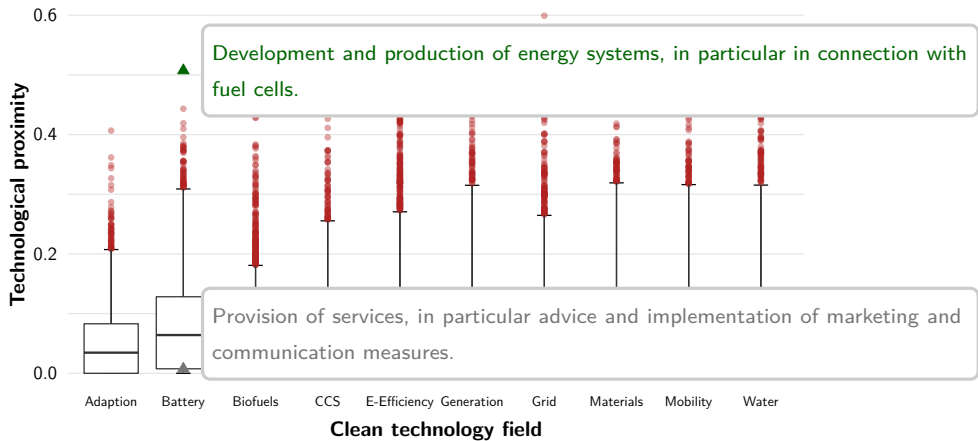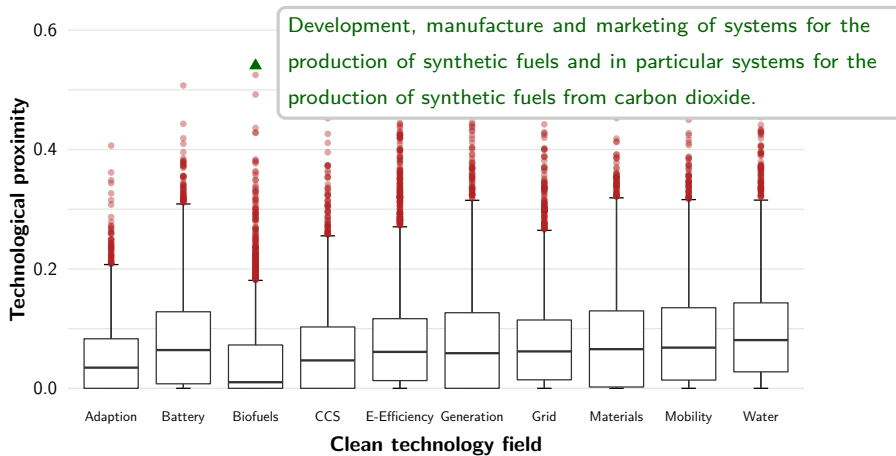
Development, manufacture and marketing of devices, processes and technologies for the reduction of anthropogenic trace substances from liquids and gases.
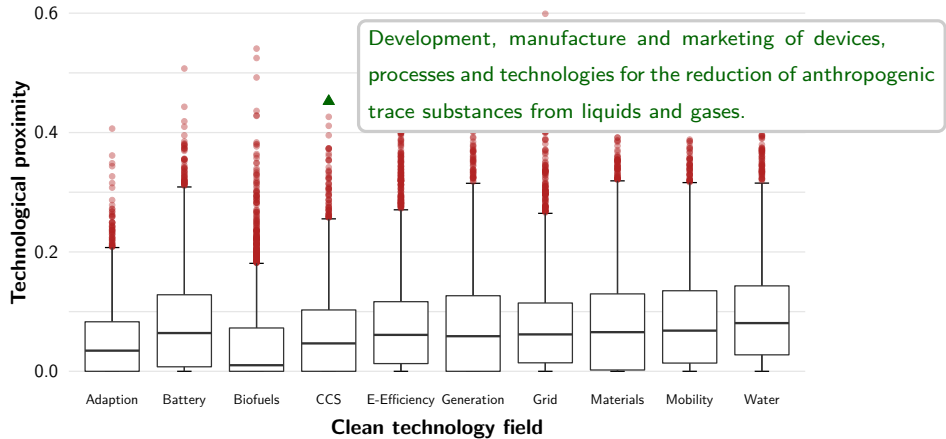
Characteristics of clean technology start-ups

Cleantech start-ups show a higher propensity to eco-innovate

	EInno					
	(1)	(2)	(3)	(4)	(5)	(6)
TECHPROX	1.015*	1.014*	1.013*	1.013*	1.012*	1.014***
log(size)		1.190***	1.140***	1.125***	1.186***	1.175***
age		1.001	1.010	1.001	1.005	1.012
subsidy			1.317***	1.353***	1.413***	1.456***
R&D			1.427***	1.434***	1.605***	1.675***
R&D intensity			0.780	0.910	0.904	0.815
returns				1.743***	1.633**	1.551**
break even				1.295***	1.226**	1.237**
team size					0.899**	0.887**
university					0.614***	0.627***
Sector controls	Y	Y	Y	Y	Y	Y
Product type controls	N	N	N	N	N	Y
N	3,269	3,269	3,269	3,192	3,192	2,774
Pseudo R^2	0.022	0.026	0.030	0.033	0.041	0.047

Note:

EInno := Introduction of environmental innovation?

- no environmental innovation
- environmental innovation with moderate environmental effect
- environmental innovation with substantial environmental effect

Coefficient estimates reported as proportional odds ratios. Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Summary

- Latest evolutions in the field of NLP allow fine granular determination of a firm's technological profile
- Legal obligation to publish a business purpose makes the technology mapping possible for start-ups even w/o traditional innovation data

- Leveraging the introduced technology mapping to the field of clean technologies suggests:
  - a high propensity of cleantech start-ups to introduce eco-innovations
  - supporting their special role in the transition to a green economy derived from theory
  - both by virtue of their business models as well as a high propensity to adopt additional environmental innovations

Acs, Z. J., & Audretsch, D. B. (2005). Entrepreneurship, Innovation and Technological Change. Now Publishers Inc.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. Journal of Political Economy, 124(1), 1–51. https://doi.org/10.1086/684581

Aharonson, B. S., & Schilling, M. A. (2016). Mapping the technological landscape: Measuring technology distance, technological footprints, and technology evolution. Research Policy, 45(1), 81–96. https://doi.org/10.1016/j.respol.2015.08.001

Bengio, Y., Ducharme, R., Vincent, P., & Jauvin, C. (2003). A Neural Probabilistic Language Model. Journal of Machine Learning Research, 3, 1137–1155. https://doi.org/10.1080/1536383X.2018.1448388

Benner, M. J. (2009). Dynamic or static capabilities? Process management practices and response to technological change. Journal of Product Innovation Management, 26(5), 473–486. https://doi.org/10.1111/j.1540-5885.2009.00675.x

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. Journal of Machine Learning Research, 3, 993–1022. https://doi.org/10.1145/2133806.2133826

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching Word Vectors with Subword Information. Transactions of the Association for Computational Linguistics, 5arXiv 1607.04606, 135–146. https://doi.org/10.1162/tacl_a_00051

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv 1810.04805. https://doi.org/10.48550/arXiv.1810.04805

Dijk, M., Wells, P., & Kemp, R. (2016). Will the momentum of the electric car last? Testing an hypothesis on disruptive innovation. Technological Forecasting and Social Change, 105, 77–88. https://doi.org/10.1016/j.techfore.2016.01.013

European Commission. (2019). The European Green Deal. https://doi.org/10.2307/j.ctvd1c6zh.7

Firth, J. R. (1957). A synopsis of linguistic theory, 1930-1955. http://annabellelukin.edublogs.org/files/2013/08/Firth-JR-1962-A-Synopsis-of-Linguistic-Theory-wfihi5.pdf

Gottschalk, S. (2013). The Research Data Centre of the Centre for European Economic Research (ZEW-FDZ). Journal of Contextual Economics – Schmollers Jahrbuch, 133(4), 607–618.

Graham, S. J., Merges, R. P., Samuelson, P., & Sichelman, T. (2009). High Technology Entrepreneurs and the Patent System : Results of the 2008 Berkeley Patent Survey Author (s): Stuart J . H . Graham , Robert P . Merges , Pam Samuelson and Ted Sichelman Published by : University of California , Berkeley , School of Law S. Berkeley Technology Law Journal, 24(4), 1255–1327.

Graham, S. J., & Sichelman, T. (2008). Why Do Start-ups Patent? Berkeley Technology Law Journal, 23(3), 1063–1097.

Helmers, C., & Rogers, M. (2011). Does patenting help high-tech start-ups? Research Policy, 40(7), 1016–1027. https://doi.org/10.1016/j.respol.2011.05.003

Hoenig, D., & Henkel, J. (2015). Quality signals? the role of patents, alliances, and team experience in venture capital financing. Research Policy, 44(5), 1049–1064. https://doi.org/10.1016/j.respol.2014.11.011

Howard, J., & Ruder, S. (2018). Universal language model fine-tuning for text classification. In Proceedings of the 56th annual meeting of the association for aomputational linguistics. https://doi.org/10.48550/arXiv.1801.06146

Jaffe, A. B. (2021). Patent Metrics for Innovation Research. (September).

Joulin, A., Grave, E., Bojanowski, P., & Mikolov, T. (2017). Bag of tricks for efficient text classification. Proceedings of the 15th conference of the European chapter of the association for computational linguistics, 2(Short Papers), 427–431. https://doi.org/10.1176/appi.ps.201500423

Mann, R. J. (2005). Texas Law Review. Texas Law Review, 83(4).

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., & Dean, J. (2013). Distributed Representations ofWords and Phrases and their Compositionality. Advances in neural information processing systems, arXiv 1606.08359, 3111–3119. https://doi.org/10.18653/v1/d16-1146

Patel, P., & Pavitt, K. (1997). The technological competencies of the world's largest firms: Complex and path-dependent, but not much variety. Research Policy, 26(2), 141–156. https://doi.org/10.1016/S0048-7333(97)00005-X

Pennington, J., Socher, R., & Manning, C. D. (2014). GloVe: Global Vectors for Word Representation Jeffrey. Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), 1532–1543. https://doi.org/10.1080/02688697.2017.1354122

Peters, M. E., Neumann, M., Iyyer, M., & Gardner, M. (2018). Deep contextualized word representations. Proceedings of the 2018 conference of the north American chapter of the association for computational linguistics: 1(Long Paper), arXiv 1802.05365, 2227–2237.

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving Language Understanding by Generative Pre-Training. https://doi.org/10.4310/HHA.2007.v9.n1.a16

Ramage, D., Hall, D., Nallapati, R., & Manning, C. D. (2009). Labeled LDA: A supervised topic model for credit attribution in multi-labeled corpora. Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing, 248–256. http://www.aclweb.org/anthology/D09-1026

Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence embeddings using Siamese BERT-Networks. In Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international Stroudsburg, PA, USA, Association for Computational Linguistics. https://doi.org/10.18653/v1/D19-1410

Sick, N., Nienaber, A. M., Liesenkötter, B., vom Stein, N., Schewe, G., & Leker, J. (2016). The legend about sailing ship effects – Is it true or false? The example of cleaner propulsion technologies diffusion in the automotive industry. Journal of Cleaner Production, 137, 405–413. https://doi.org/10.1016/j.jclepro.2016.07.085

United Nations. (2015). Paris Agreement. Retrieved October 1, 2020, from
       https://unfccc.int/sites/default/files/english%7B%5C_%7Dparis%7B%5C_%7Dagreement.pdf
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017).
       Attention Is All You Need. 31st Conference on Neural Information Processing Systems (NIPS 2017), arXiv
       1706.03762. http://arxiv.org/abs/1706.03762
Wang, Y., Hou, Y., Che, W., & Liu, T. (2020). From static to dynamic word representations: a survey.
       International Journal of Machine Learning and Cybernetics, 11(7), 1611–1630.
       https://doi.org/10.1007/s13042-020-01069-8

Appendix
Technology-company mapping framework

"Developer of carbon capture systems."

	INPUT					
Tokenization	[CLS] **developer**	**of**	**carbon**	**capture**	**systems**	[SEP]
Vocab indices	[0, 239,	1221,	155,	87,	977,	1]
Embeddings ($Q\times1$)	[[0.23, -0.07, 0.01, ...]′, [-0.42, 0.03, -0.77, ...]′, [...], [...], [...], [...], [-0.03, -0.23, ...]′]					

BERT

ENCODER 1

BERT

ENCODER 1

Self-Attention

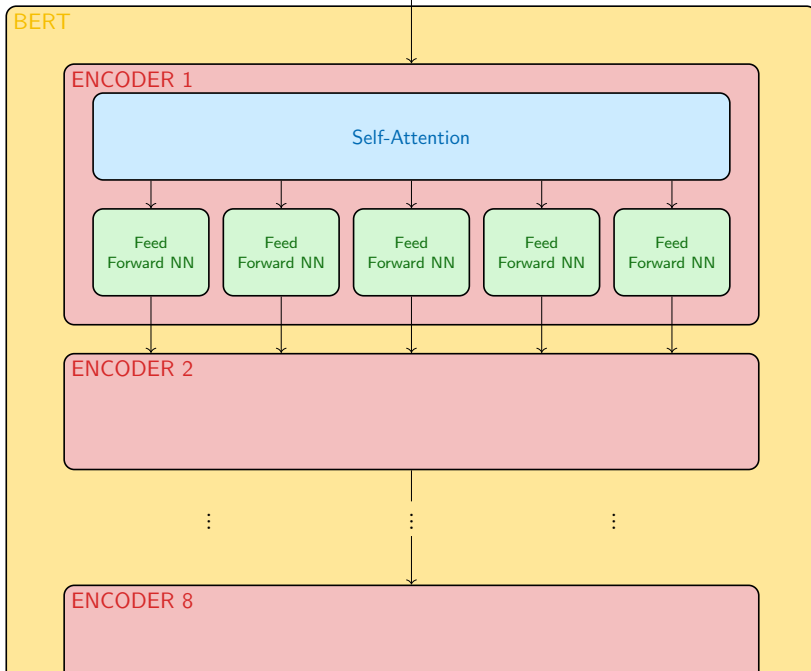Feed Forward NN | Feed Forward NN | Feed Forward NN | Feed Forward NN | Feed Forward NN

ENCODER 2

ENCODER 8

ENCODER 6

Contextualized
Embeddings
(Q×1)

OUTPUT

$[[$-0.03, 0.98, 0.22, ...$]'$, $[$-0.12, 0.78, 0.54, ...$]'$, $[...]$, $[...]$, $[...]$, $[...]$, $[$-0.83, -0.11, ...$]'$$]$

w_1	w_2	w_3	w_4	w_5
developer	**of**	**carbon**	**capture**	**systems**
[-0.42, 0.03, -0.77, ...]'	[...]	[...]	[...]	[...]

SELF-ATTENTION

SELF-ATTENTION

Keys

k_1 k_2 k_3 k_4 k_5

Values

v_1 v_2 v_3 v_4 v_5

0.4 0.3 .05 .05 0.2

Attention weights a_1

0.4 0.3 .05 .05 0.2

q_1
Query

$\hat{z}_1$
Output

q_1
Query

$\hat{z}_1$
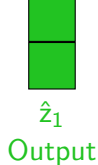Output
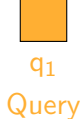
1. Attention weights $a_{1:5}$ are query-key similarities:
$$\hat{a}_i = \mathbf{q}_i \times \mathbf{k}_i$$
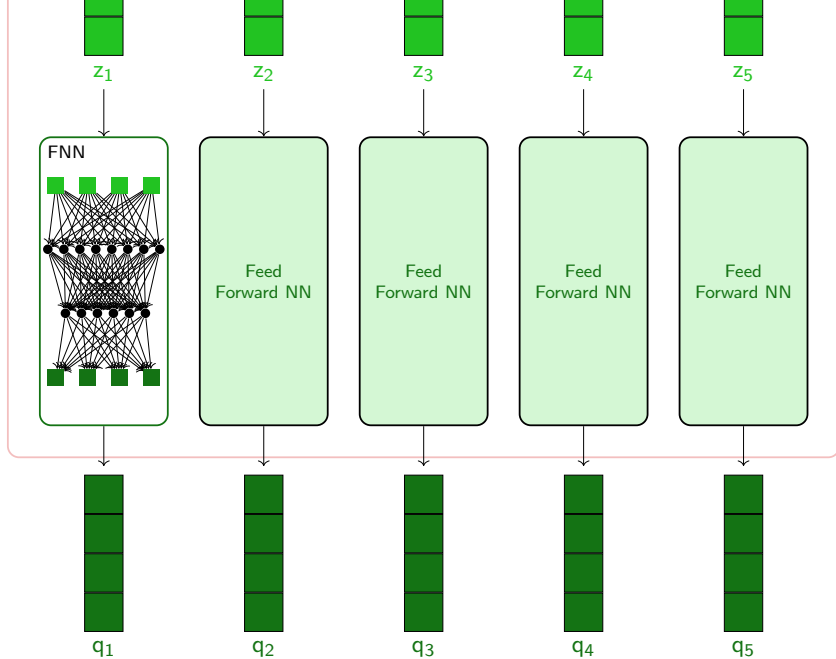   Normalized via softmax: $a_i = e^{\hat{a}_i} / \sum_j e^{\hat{a}_j} \in [0,1]$

2. Output $\underset{(1 \times Z)}{\widehat{\mathbf{z}}_i}$ is attention-weighted average of value vectors $\mathbf{v}_{1:5}$:
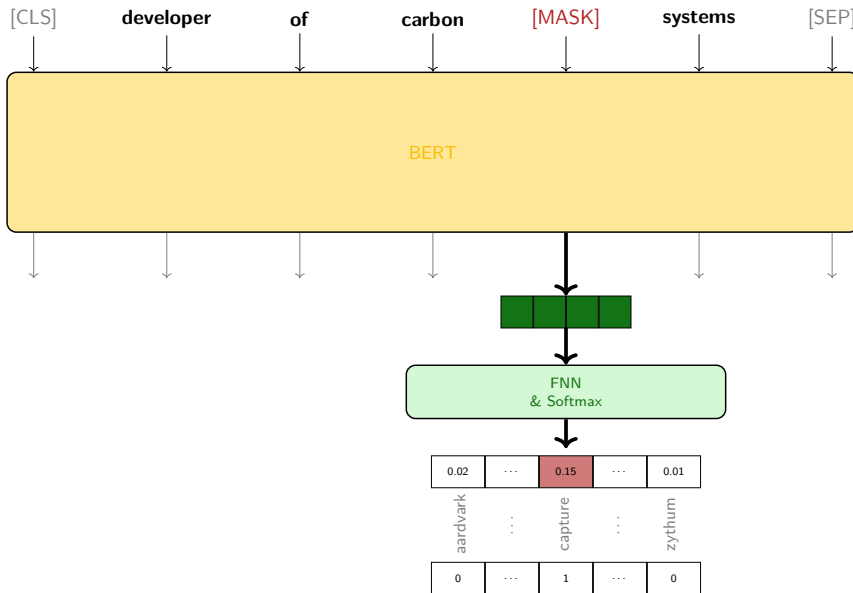$$\widehat{\mathbf{z}}_i = \sum_i a_i \mathbf{v}_i$$

3. $\mathbf{k}$, $\mathbf{v}$ and $\mathbf{q}$ are derived from the entire input $\mathbf{w}$:
$$\mathbf{k} = W_k \times \mathbf{w} \qquad \mathbf{v} = W_v \times \mathbf{w} \qquad \mathbf{q} = W_q \times \mathbf{w}$$

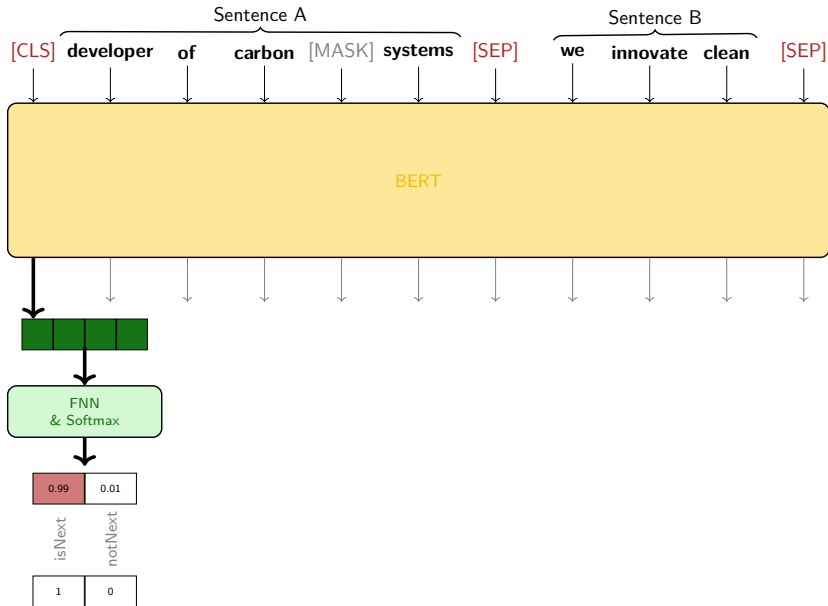Note: Self-attention is repeated H times (multi-head attention) and the resulting vectors are concatenated along the feature dimension. Multiplying with a weight matrix $\underset{(Q \times HZ)}{W_z}$ yields the final output vector that is passed to the FNN.

z_1 z_2 z_3 z_4 z_5

FNN

Feed Forward NN   Feed Forward NN   Feed Forward NN   Feed Forward NN

q_1 q_2 q_3 q_4 q_5

1. Masked language modeling

[CLS]   **developer**   **of**   **carbon**   [MASK]   **systems**   [SEP]

BERT

FNN
& Softmax

0.02	$\cdots$	0.15	$\cdots$	0.01
aardvark	$\vdots$	capture	$\vdots$	zythum
0	$\cdots$	1	$\cdots$	0

2. Next sentence prediction

q_A

q_B

q_A q_B $|q_A - q_B|$

Softmax

| 0.02 | 0.97 | 0.01 |

contra-diction | entailment | neutral

| 0 | 1 | 0 |

Invention, Innovation & Entrepreneurship

A patent reflects new technical knowledge, but it does not indicate whether this knowledge has a positive economic value. Only those inventions which have been successfully i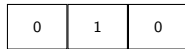ntroduced in the market can claim that they are innovations as well. While innovations and inventions are related, they are not identical.

Acs et al. (2005)

Text preprocessing

1. translation of non-English texts to English
2. Part of Speech (PoS) tagging
    2.1 remove punctuation, numbers and unknown tags
    2.2 lemmatization
3. stop word deletion

A labeled corpus of patent abstracts

Patent	Technology class	Abstract
1	B, C, Y02C, Y02P	Catalyst, comprising one or more compounds of the perovskite-type as catalytically active component, is new, where the catalytically active component in the form of at least one layer is applied on a support body from an open cell foam ceramic material ...
2	A, Y02A, Y02C, Y02E	Absorber fluid, comprises a carbon dioxide binding absorbent and an ionic additive in a concentration, which is greater than a minimum concentration, so that the activity of the products formed by the connection of carbon dioxide to the absorbent is reduced ...
$\vdots$	$\vdots$	$\vdots$
P	B, F, Y02C	The invention relates to a power plant for generating electrical energy, comprising a combustion chamber for producing steam, at least one waste gas purification stage that is connected downstream, a separation stage for CO2 ...

Note: Corpus comprises $P \sim 560,000$ patents (all patents filed by German firms after 1990) and a vocabulary size of $V \sim 370,000$ (after text preprocessing).

Vertical differentiation in technology classes

Classification system of the European Patent Office using the example of **carbon capture and storage technologies**:

CPC	COOPERATIVE PATENT CLASSIFICATION
Y	New technological developments
Y02	Climate change mitigation technologies
Y02C	Carbon capture and storage technologies
Y02C20	Capture and disposal of greenhouse gases
Y02C20/10	- of N_2O

Latent Dirichlet Allocation

Core idea in Blei et al. (2003) seminal work on Latent Dirichlet Allocation (LDA):
Model the generative process that led to the creation of a text corpus incorporating both:

- the observed words in the corpus' documents

- *and* the hidden topic structure within the corpus

in the imaginary data generating process.

The latter includes the distribution of topics over documents and the word distributions over topics.

Latent Dirichlet Allocation

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- the observed words in the corpus' documents

- *and* the hidden topic structure within the corpus

in the imaginary data generating process.

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L-LDA (Ramage et al., 2009) extents upon LDA by taking into consideration document labelsin the generative process.

L-LDA in patent corpus:

- document $\hat{=}$ patent, p

- labels/topics $\hat{=}$ technology classes, t

- word distributions over topics $\hat{=}$ semantic technology description, $p(\delta_t)$

Statistical Learning in L-LDA

Patent corpus D consisting of P distinct patent abstracts each of length N_p, generative process can be modeled as follows:

1. For each technology class $t \in \{1, \ldots, T\}$: generate word distribution $\delta_t \sim Dir(\beta)$

2. For each patent $p \in \{1, \ldots, P\}$: generate technology class distribution $\lambda_p \sim Dir(\alpha_p)$

3. For each of the word positions p, n, with $p \in \{1, \ldots, P\}$ and $n \in \{1, \ldots, N_p\}$:
   - 3.1 generate technology class assignment $z_{p,n} \sim Multinomial(\lambda_p)$
   - 3.2 and choose word $w_{p,n} \sim Multinomial(\delta_{z_{p,n}})$

$$p(\delta_{1:T}, \lambda_{1:P}, z_{1:P}, w_{1:P}) = \prod_{t=1}^{T} p(\delta_t) \prod_{p=1}^{P} p(\lambda_p) \left(\prod_{n=1}^{N_p} p(z_{p,n}|\lambda_p) p(w_{p,n}|\delta_{z_{p,n}}) \right)$$

Goal: Derive posterior distribution $p(\delta_t)$ from joint distribution $p(\delta_{1:T}, \lambda_{1:P}, z_{1:P}, w_{1:P})$

Importance of capture contextual meaning of words

- **technical terms** in technology descriptions:
  $X_t = \langle$ gas, absorb, carbon, dioxide, desorption ... $\rangle$

- **non-technical terms** in company descriptions:
  '*Developer of direct air capture technology that safely and permanently removes CO2 from the air.*
  $\rightarrow Y_c = ($developer, direct, air, technology, safe, permanent, remove, co2$)$'

- **But**: high semantic overlap between x_t and y_c as captured by token embeddings
  $\bar{X}_t(carbon) \approx \bar{Y}_c(co2)$
  $\bar{X}_t(absorb) \approx \bar{Y}_c(remove)$

- **Goal**: Exploit these relations to capture adopters of a technology

Classification performance of TECHPROX

Table: Performance of TECHPROX in distinguishing cleantech from non-cleantech firms

Label	Precision	Recall	F1-Score	Support
Cleantech	0.87	0.86	0.86	284
Non-cleantech	0.83	0.84	0.83	233
			0.85	517

Note: Performance measured on random test set with optimal values of $Q = 15$ and $\text{TECHPROX}_{min} = 0.27$. Optimal values for Q and TECHPROX_{min} have been determined on the validation set by tuning F1-Score.

Evolution of NLP
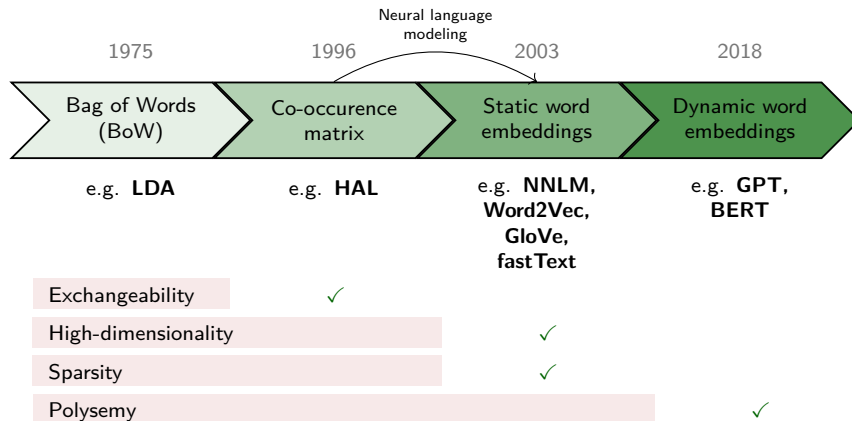
Word embeddings (1)

You shall know a word by the company it keeps!

Firth (1957)

General idea: exploit information on co-occurrence of words in large text corpora in order to learn the semantic meaning of a word as represented by a low-dimensional, dense vectors ($E \ll V$).

Natural Language Processing (NLP) as highly active field of research with major advances in recent years (see Wang et al. (2020)):

Neural Network Language Models

- 'distributed representation for words' (Bengio et al., 2003)
    - learn model that predicts next word given previous words
    - word embeddings carrying semantic meaning of a word as by-product

Word embeddings (2)

Static word embeddings

- ‣ Word2Vec (Mikolov et al., 2013)

    - ‣ neural network architecture specifically designed to learn word embeddings
    - ‣ Continuous Bag-of-Words (CBOW): predict word given its surrounding context words
    - ‣ Skipgram: predict context words given central word

- ‣ GloVe (Pennington et al., 2014)

    - ‣ direct exploitation of co-occurence statistics from large text corpora

- ‣ fastText (Bojanowski et al., 2017; Joulin et al., 2017)

    - ‣ learning embeddings for character n-grams and representing words as the sum of the n-gram embeddings (towards multi-language models)
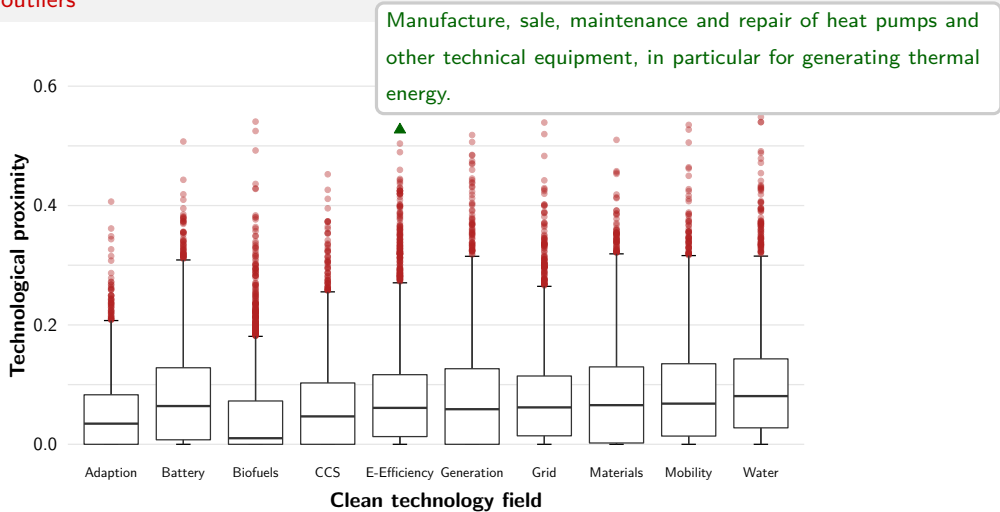
Word embeddings (3)

Contextualized word embeddings
Tackle the issue that words have different meanings in different contexts (polysemy)

- ELMo (Peters et al., 2018)
    - use bidirectional LSTM to capture whole sentence (context!) in order to model embeddings of words in sentence

- ULMFit (Howard et al., 2018)
    - introduce a general language model and a process to fine-tune to domain-specific NLP tasks

- GPT (Radford et al., 2018)
    - use transformer network architecture to learn linguistic long-term dependencies

- BERT (Devlin et al., 2018)
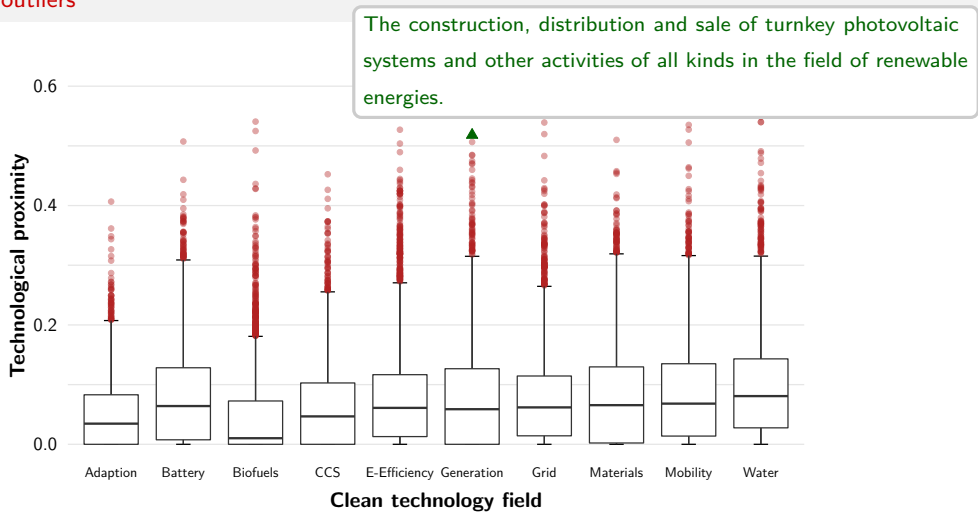   - Consider bidirectional contexts and relation of sentence pairs based on transformer encoders
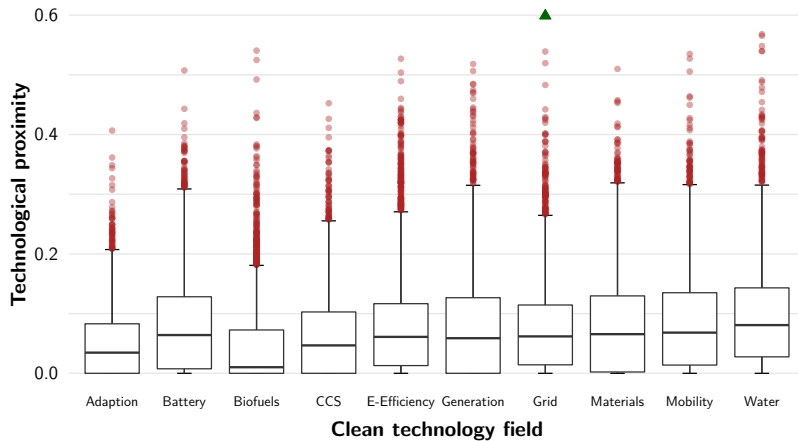
Application
A glance at the 'outliers'

Manufacture, sale, maintenance and repair of heat pumps and other technical equipment, in particular for generating thermal energy.

The construction, distribution and sale of turnkey photovoltaic systems and other activities of all kinds in the field of renewable energies.

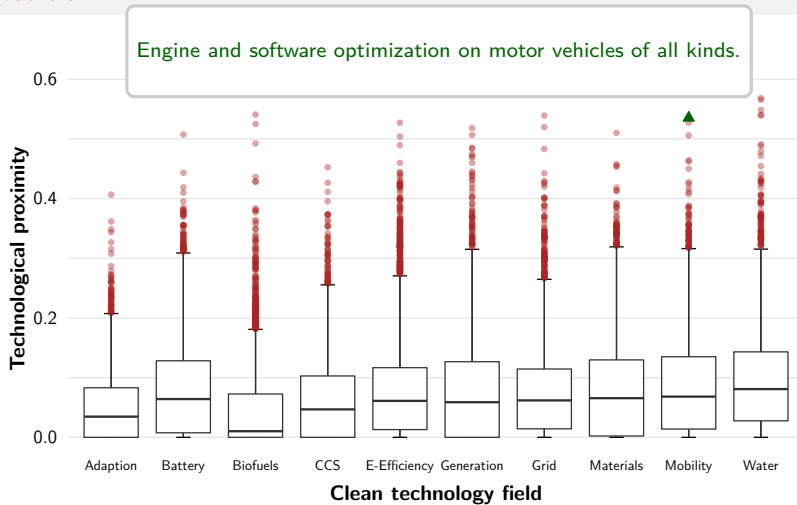# Application

Manufacture of electrode foils, lithium accumulators and energy storage systems and the provision of services in this area.
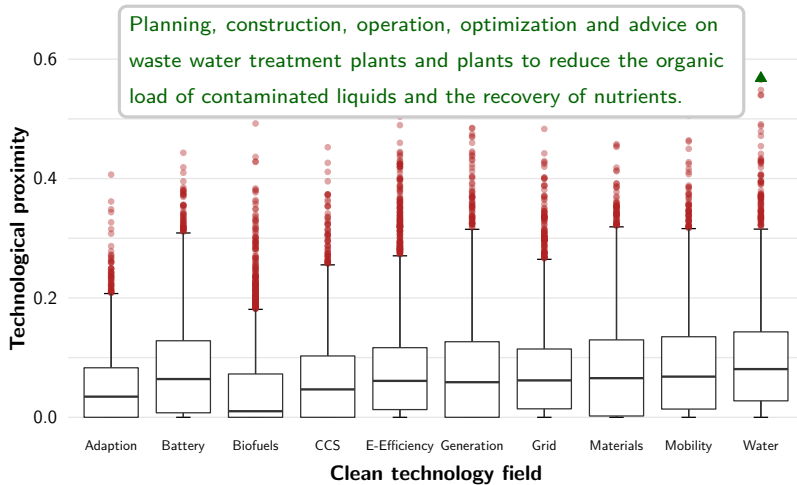
Engine and software optimization on motor vehicles of all kinds.

Application
A glance at the 'outliers'

Planning, construction, operation, optimization and advice on waste water treatment plants and plants to reduce the organic load of contaminated liquids and the recovery of nutrients.

Table: 2018 IAB/ZEW Start-up survey questions on environmental impacts and environmental innovation

Environmental impact

Does your company offer products or services which have the following environmental effects on the customer or the end user?

1. Reduction of energy consumption or CO_2 footprint for the customer.
2. Reduction of other emissions to the air, water, soil or noise for the the customer.
3. Reduction of material or resource consumption, for instance water, for the customer.
4. Improvement of recyclability of customer's products.
5. Improvement of durability of customer's products.

Environmental innovation

Since its inception, has your company introduced innovations that have impacted the environment as follows?

1. Reduction of energy consumption or the overall CO_2 balance in your company.
2. Reduction of other emissions to the air, water, soil or noise in your company.
3. Reduction of material or resource consumption, for instance water, in your company.
4. Improvement of recyclability of your own products.
5. Improvement of durability of your own products.

Note: The questions have been asked on a Likert response scale with the following response possibilities. (1) No; (2) Yes, somewhat; (3) Yes, substantial.