# 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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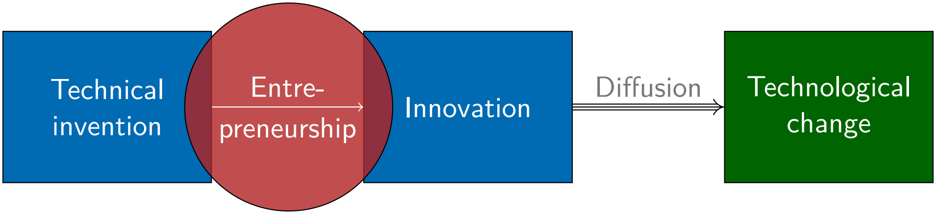

# Technological innovation and its measurement


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

Jaffe (2021)

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***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 (Mann, 2005; Graham et al., 2008; Graham et al., 2009; Helmers et al., 2011):

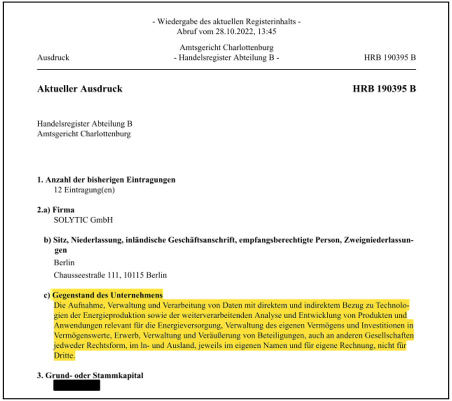
- distracting engineers/managers from key functions
- costs of patenting/patent litigation too high
- disclosure through patent allows ‘design around’

**Research question I**

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

# Textual innovation data

## New ventures legally obliged to publish business purpose at business registration



- Wiedergabe des aktuellen Registerinhalts -
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Handelsregister Abteilung B
Amtsgericht Charlottenburg

**1. Anzahl der bisherigen Eintragungen**
12 Eintragung(en)

**2.a) Firma**
SOLYTIC GmbH

**b) Sitz, Niederlassung, inländische Geschäftsanschrift, empfangsberechtigte Person, Zweigniederlassungen**
Berlin
Chausseestraße 111, 10115 Berlin

**c) Gegenstand des Unternehmens**
Die Aufnahme, Verwaltung und Verarbeitung von Daten mit direktem und indirektem Bezug zu Technologien der Energieproduktion sowie der weiterverarbeitenden Analyse und Entwicklung von Produkten und Anwendungen relevant für die Energieversorgung, Verwaltung des eigenen Vermögens und Investitionen in Vermögenswerte, Erwerb, Verwaltung und Veräußerung von Beteiligungen, auch an anderen Gesellschaften jedweder Rechtsform, im In- und Ausland, jeweils im eigenen Namen und für eigene Rechnung, nicht für Dritte.

**3. Grund- oder Stammkapital**
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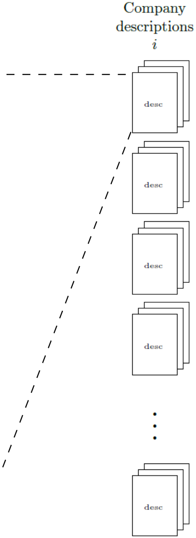
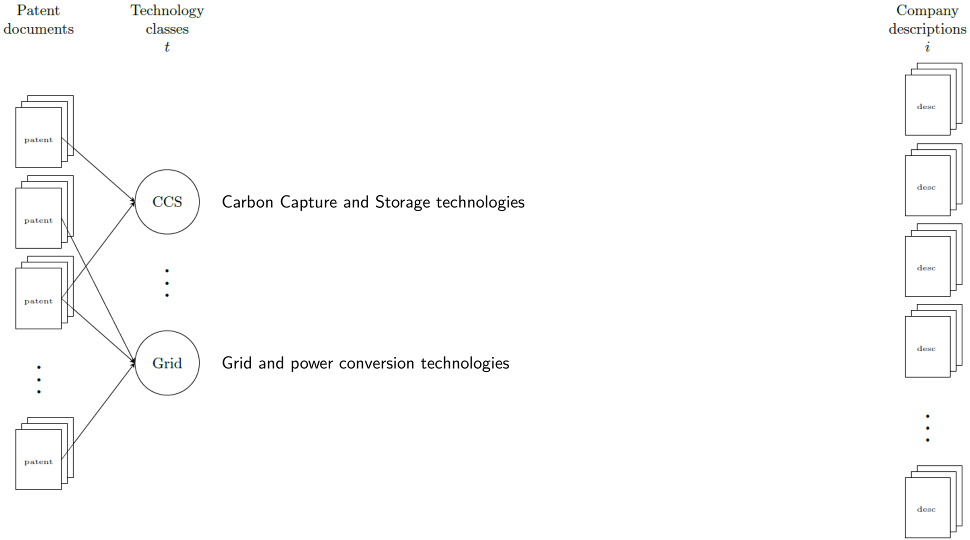


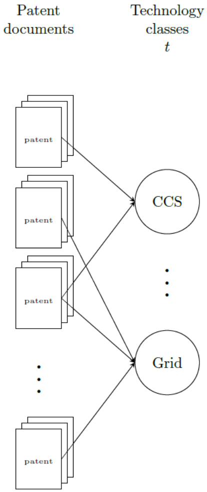
# Textual innovation data

## Patent texts and assigned technology classes

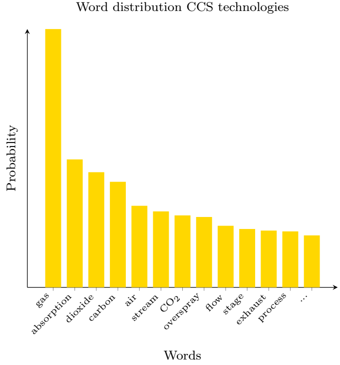


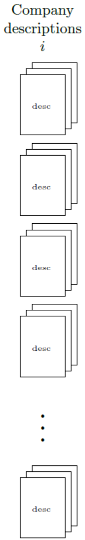
# From patents to technology descriptions

## L-LDA (Ramage et al., 2009)



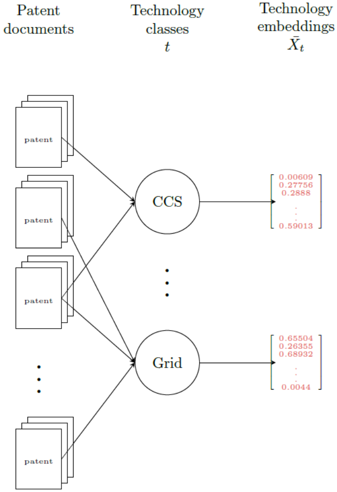

Goal: Derive technology-word distributions from expert-labeled corpus of patent docs



# Contextualized vector representations

## BERT (Devlin et al., 2018)

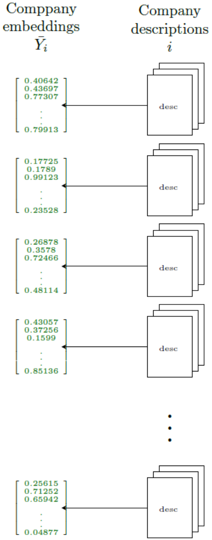



Goal: Derive contextualized vector representations of technology & business descriptions

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

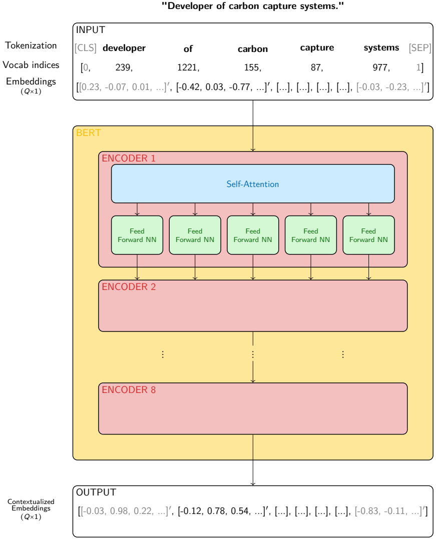
$$\Big\downarrow \text{SBERT}$$

$$\underset{(1\times 384\ \forall Q)}{X_{CCS}} = [0.006, 0.277, 0.288, \ldots 0.590]'$$



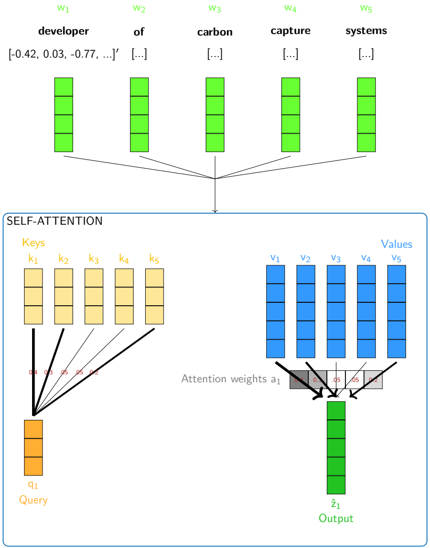
# Excursus: BERT

## Model architecture



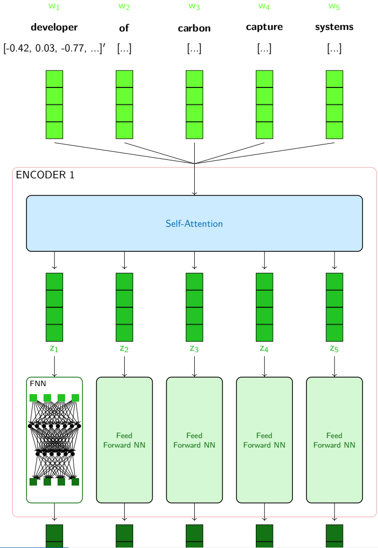
# Attention Is All You Need (Vaswani et al., 2017)

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



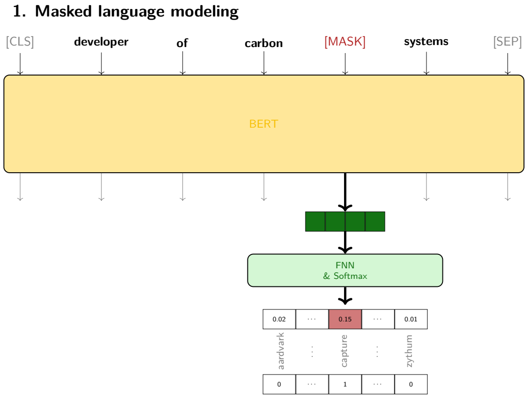
# Encoder

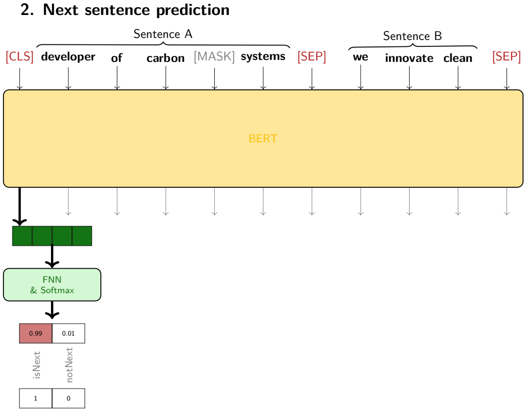
## After Attention, each token pondering for itself about what it has observed previously



# Training BERT

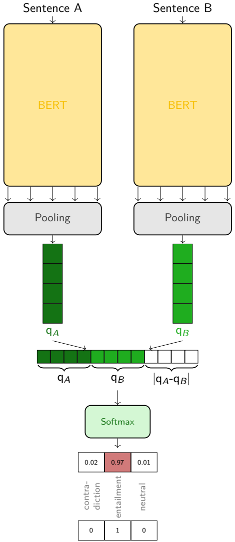
## Self-supervised learning based on English Wikipedia



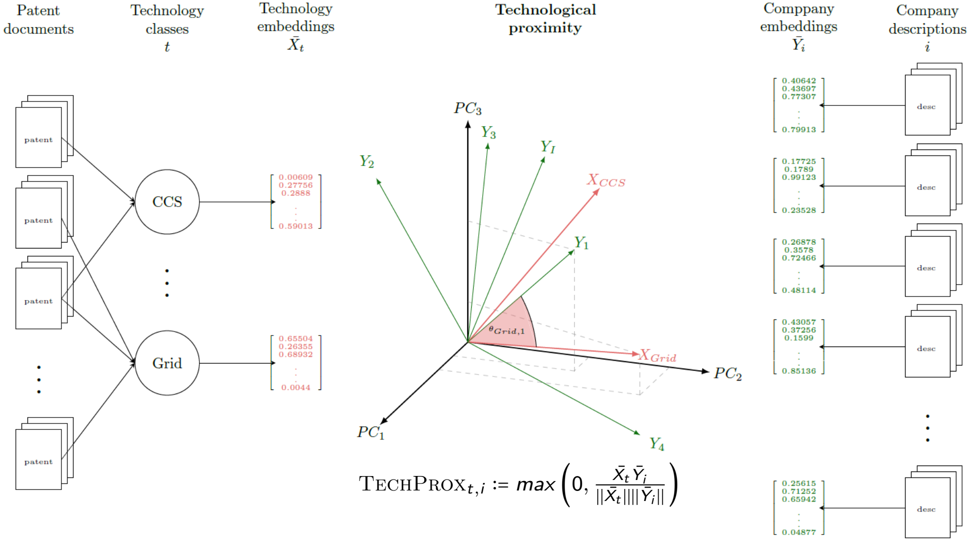
# Finetuning BERT: SBERT (Reimers et al., 2019)

## 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 capability




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

Adaptation to and mitigation of climate change requires new technological pathways and radical innovations (*inter alia* United Nations (2015), European Commission (2019))

- but: technological path dependencies and system/innovation inertia among incumbents (Patel et al., 1997; Aghion et al., 2016)
- costly: delay in redirecting innovation towards clean technologies (Benner, 2009; Dijk et al., 2016; Sick et al., 2016)

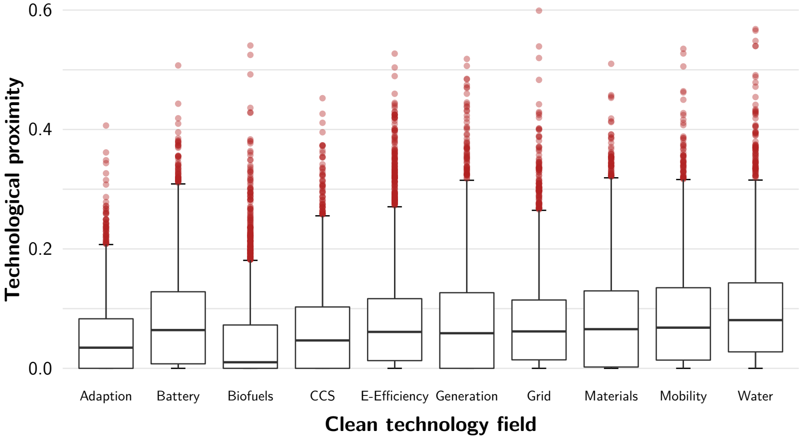
$\Rightarrow$ special role of new (path-independent!) ventures in triggering clean technology change (Cohen et al., 2007; Hockerts et al., 2010; Horne et al., 2022)

**Research question II**

Which role do start-ups play in the diffusion of clean technologies?

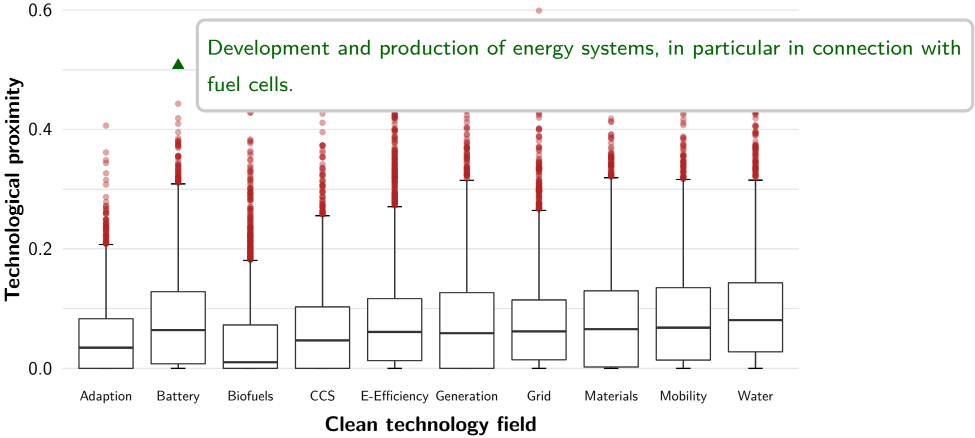
# Application

## TechProx in survey of German start-ups



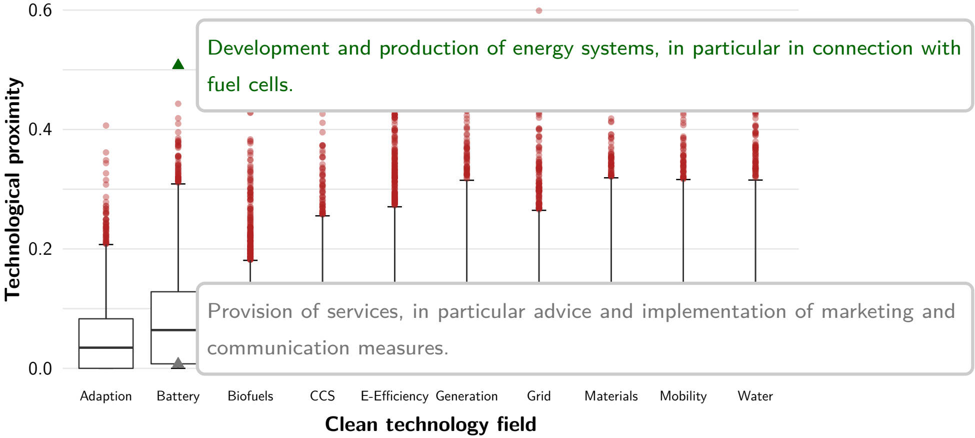
# Application

## A glance at the 'outliers'



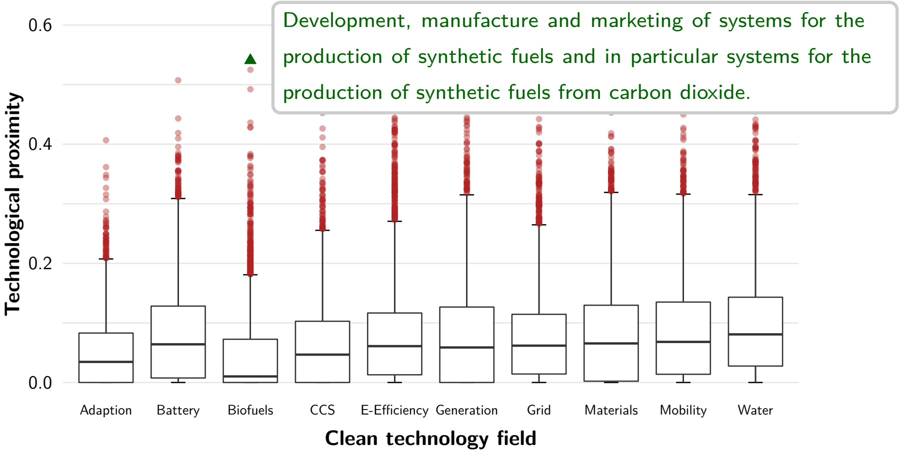
# Application

## A glance at the ‘outliers’



# Application

## A glance at the 'outliers'



# Characteristics of clean technology start-ups

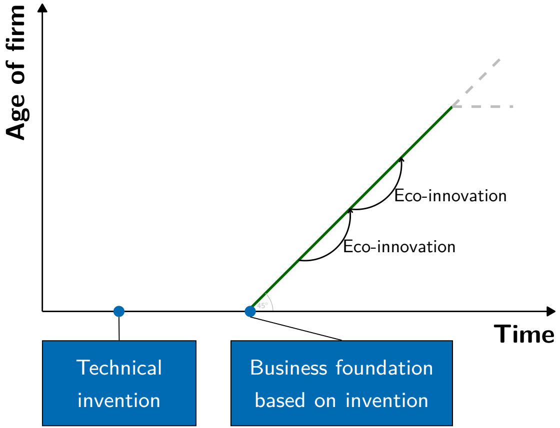
## Cleantech start-ups show a higher propensity to eco-innovate

| | *EInno* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| TechProx (0-1) | 1.339*** | 1.328*** | 1.325*** | 1.295*** | 1.288*** | 1.383*** |
| log(size) | | 1.191*** | 1.154*** | 1.129*** | 1.191*** | 1.187*** |
| subsidy | | | 1.304*** | 1.352*** | 1.411*** | 1.445*** |
| R&D | | | 1.334*** | 1.411*** | 1.574*** | 1.595*** |
| returns | | | | 1.773*** | 1.665** | 1.616** |
| break even | | | | 1.299*** | 1.232** | 1.257** |
| team size | | | | | 0.901** | 0.891** |
| university | | | | | 0.612*** | 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 $R^2$ | 0.021 | 0.025 | 0.029 | 0.033 | 0.040 | 0.047 |

*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: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

# Entrepreneurial process and innovation



# 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

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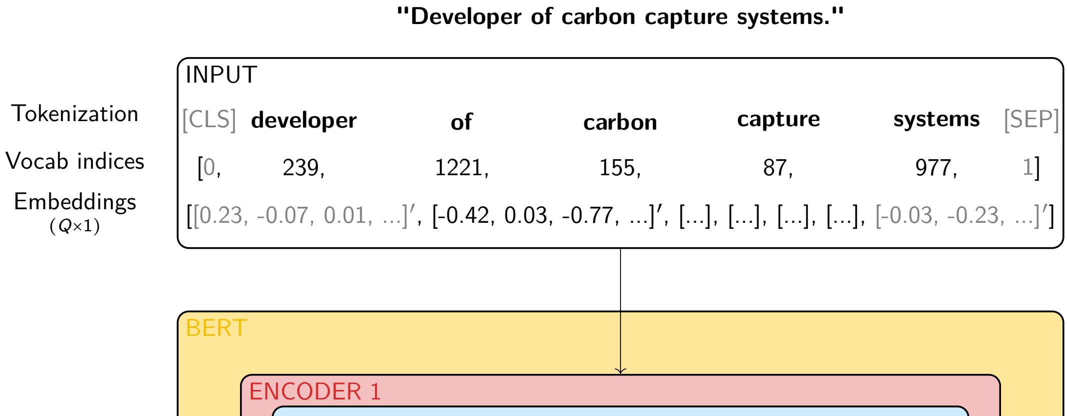
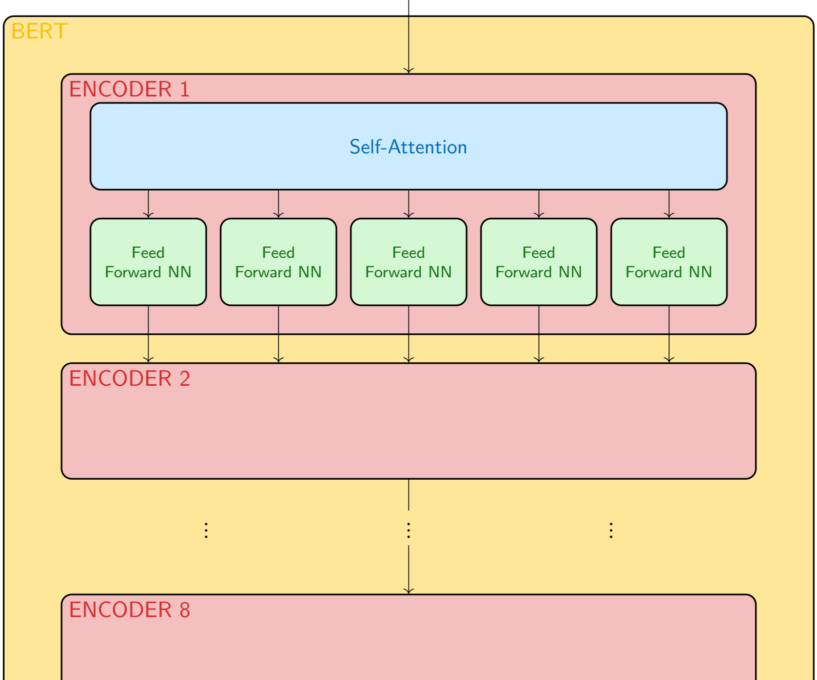
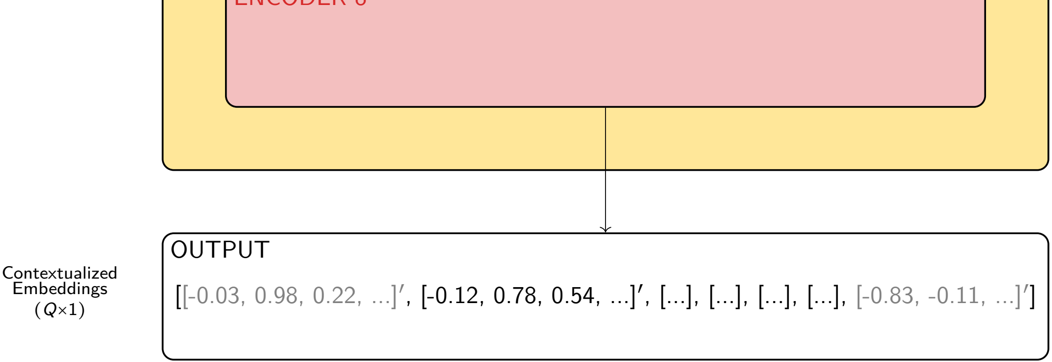
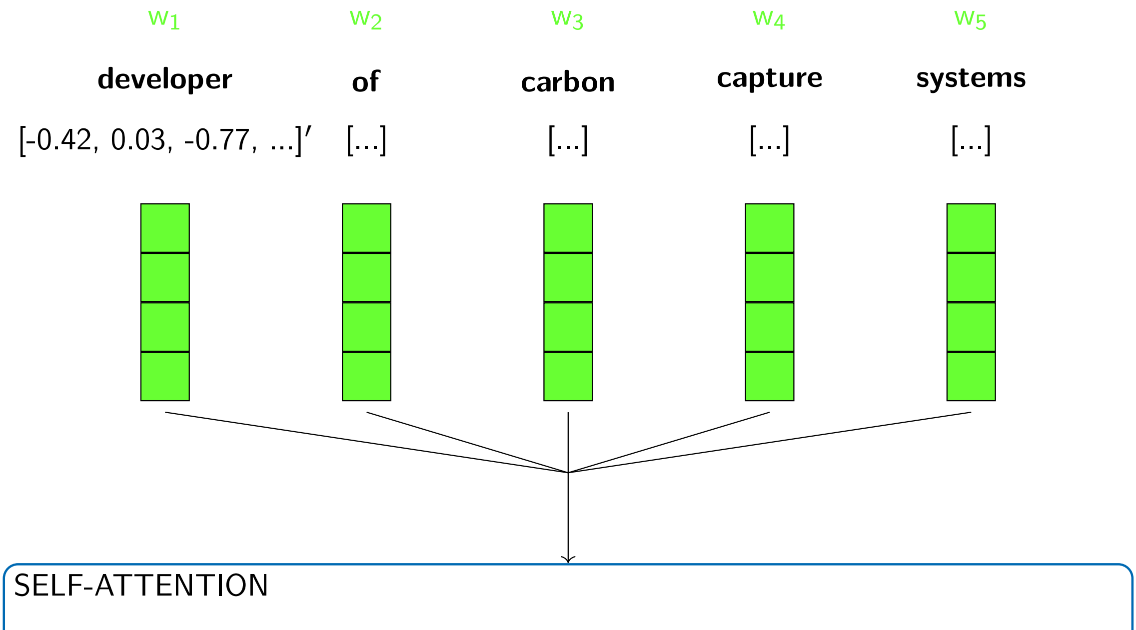
# Appendix

## Technology-company mapping framework

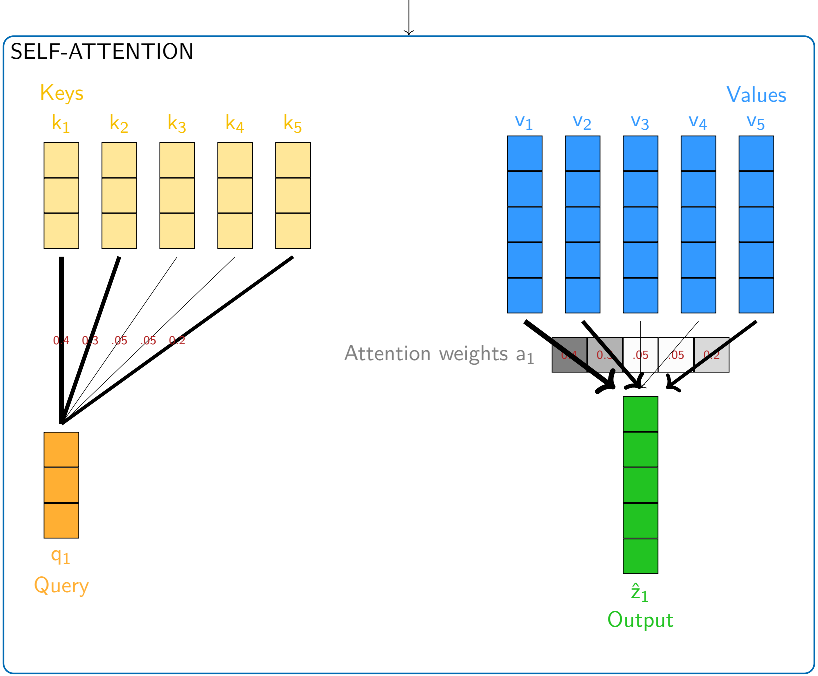

"Developer of carbon capture systems."
INPUT
Tokenization
[CLS] developer of carbon capture systems [SEP]
Vocab indices
[0, 239, 1221, 155, 87, 977, 1]
Embeddings
($Q$×1)
[[0.23, -0.07, 0.01, ...]′, [-0.42, 0.03, -0.77, ...]′, [...], [...], [...], [...], [-0.03, -0.23, ...]′]
BERT
ENCODER 1

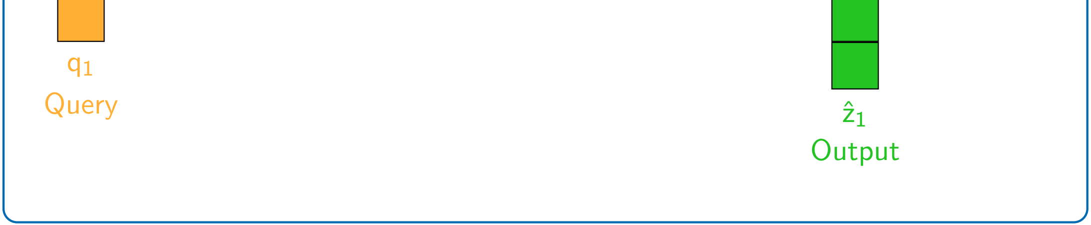

BERT
ENCODER 1
Self-Attention
Feed Forward NN
Feed Forward NN
Feed Forward NN
Feed Forward NN
Feed Forward NN
ENCODER 2
ENCODER 8


ENCODER 6
OUTPUT
Contextualized Embeddings ($Q$×1)
[[-0.03, 0.98, 0.22, ...]′, [-0.12, 0.78, 0.54, ...]′, [...], [...], [...], [...], [-0.83, -0.11, ...]′]



w1
w2
w3
w4
w5
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




1. Attention weights $a_{1:5}$ are query-key similarities:

   $\hat{a}_i = \mathbf{q}_i \times \mathbf{k}_i$

   Normalized via softmax: $a_i = e^{\hat{a}_i} / \sum_j e^{\hat{a}_j} \;\in [0, 1]$

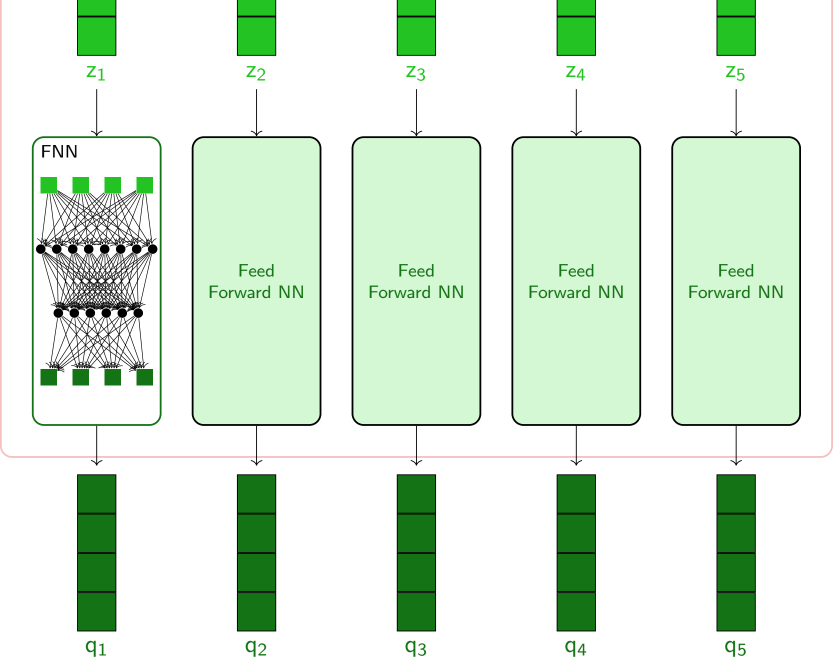
2. Output $\underset{(1 \times Z)}{\widehat{\mathbf{z}}_i}$ is attention-weighted average of value vectors $\mathbf{v}_{1:5}$:

   $\widehat{\mathbf{z}}_i = \sum_i a_i \mathbf{v}_i$

3. $\mathbf{k}$, $\mathbf{v}$ and $\mathbf{q}$ are derived from the entire input $\mathbf{w}$:

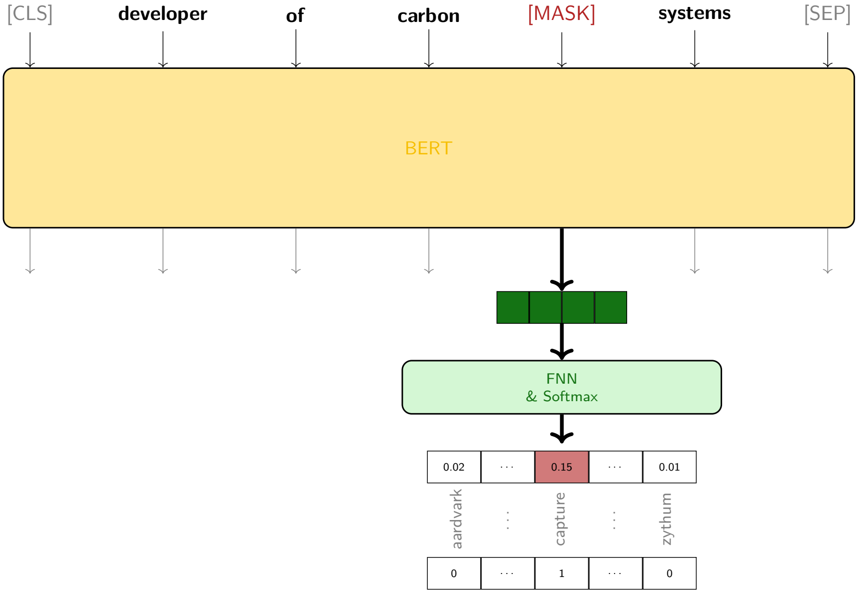
   $\mathbf{k} = W_k \times \mathbf{w} \qquad \mathbf{v} = W_v \times \mathbf{w} \qquad \mathbf{q} = W_q \times \mathbf{w}$

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.

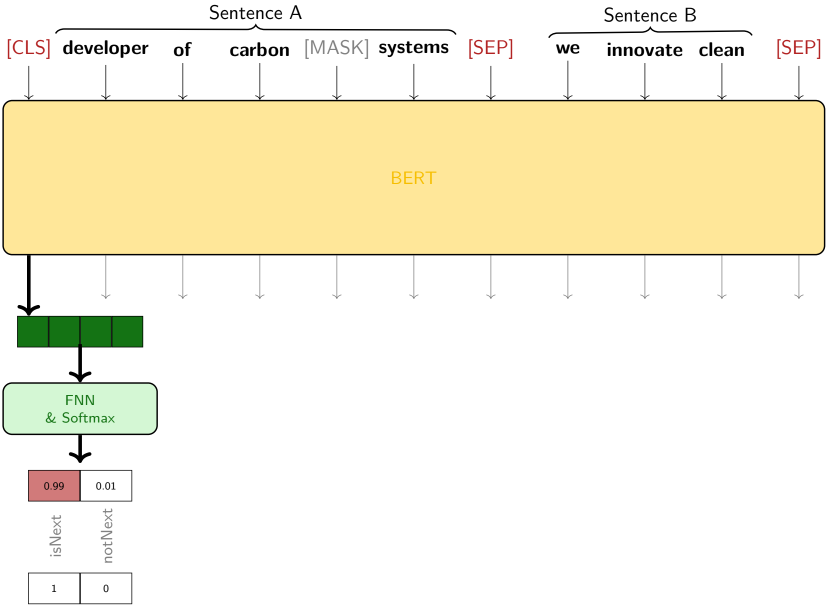


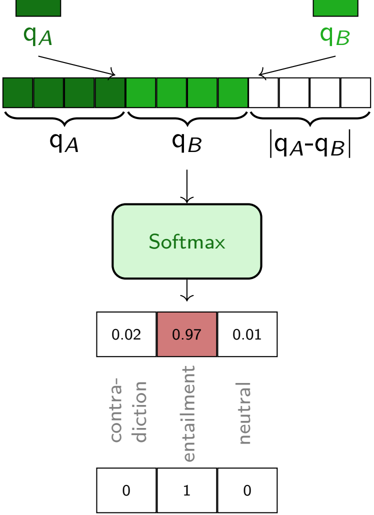
$z_1$
$z_2$
$z_3$
$z_4$
$z_5$
FNN
Feed Forward NN
Feed Forward NN
Feed Forward NN
Feed Forward NN
$q_1$
$q_2$
$q_3$
$q_4$
$q_5$

# 1. Masked language modeling



## 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 introduced 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 ... |
| ⋮ | ⋮ | ⋮ |
| $P$ | 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).

# Clean technology classes by European Patent Office (EPO)

| | Clean technology field | | Technology example |
|---|---|---|---|
| 1 | Adaption | Technologies for the adaption to climate change | Genetically modified plants resistant to drought |
| 2 | Battery | Battery storage and fuel cells | Fuel cell technologies in production processes |
| 3 | Biofuels | Biofuel technologies | Algae biomass |
| 4 | CCS | Carbon capture, storage and sequestration | Enhanced coal bed methane recovery |
| 5 | E-efficiency | Energy efficiency | Insulation technologies inhibiting radiant heat transfer |
| 6 | Generation | Renewable energy generation | Generation of geothermal energy |
| 7 | Grid | Grid and power conversion | Smart grids |
| 8 | Materials | Low carbon materials and manufacturing | Technologies to replace cement by fly ash in concrete production |
| 9 | Mobility | Electric vehicles and low carbon mobility solutions | Ultracapacitors for efficient electric vehicle charging |
| 10 | Water | Water and wastewater treatment | Technologies for the production of fertilisers from the organic fraction of waste or refuse |

Note: Clean technology fields form the basis for deriving a mapping between specific clean technologies and business models. Patent documents labeled with the corresponding CPC classes by the EPO as listed in the last column are used to derive semantic representations of the respective clean technology field.

# 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.

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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, $\delta_t$

# 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 $w_{p,n} \sim Multinomial(\delta_{z_{p,n}})$

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

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

# Gibbs Sampling (1)

$$\underbrace{p(z_{p,n} = t | \mathbf{z}_{p,-n})}_{\substack{\text{Probability that technology } t \\ \text{is chosen for position } n \text{ in patent } p \\ \textbf{conditioned} \text{ on all other} \\ \text{technology-position assignments in the patent}}} \propto \frac{\overbrace{C^{WT}_{w_n,t,-n}}^{\substack{\text{Count of word } w_n \\ \text{in technology } t \\ \text{not including the} \\ \text{current assignment } z_n}} + \beta}{\sum_{i=1}^{N_p} C^{WT}_{w_i,t,-n} + V\beta} \times \frac{\overbrace{C^{WP}_{p,t,-n}}^{\substack{\text{Count of technology } t \\ \text{having already been assigned} \\ \text{to some position in patent } p \\ \text{not including the} \\ \text{current assignment } z_n}} + \alpha_p}{\sum_j^T C^{WP}_{p,j,-n} + T\alpha_p}$$

- $C^{WT}$: Word-technology count matrix
- $C^{WP}$: Word-patent count matrix
- $V$: Vocabulary size
- $T$: Number of distinct technologies

# Gibbs Sampling (2)

Iteratively draw new technology position attributions according to the above probability and update the topic assignment list with the newly sampled topic for token $z_n$ and re-increment the word-topic and document-topic count matrices with the new sampled topic for token $z_n$.

After sufficient iterations the probability of a word given a technology can be calculated as follows:

$$\delta_{n,t} = \frac{C^{WT}_{w_n,t} + \beta}{\sum_{i=1}^{V} C^{WT}_{w_i,t} + V\beta}$$

# Importance of capture contextual meaning of words

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

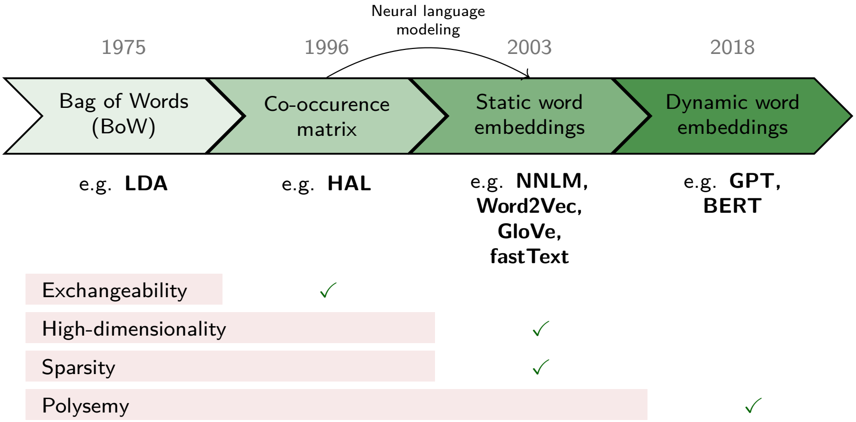
# Classification performance of TechProx

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 $\text{TechProx}_{min}$ 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)

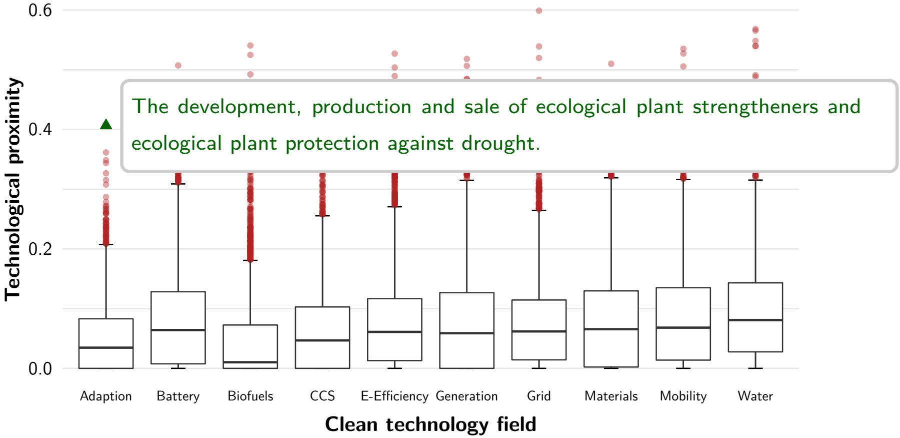
**Contextualized word embeddings**

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 decoders to learn linguistic long-term dependencies
- BERT (Devlin et al., 2018)
  - Consider bidirectional contexts and relation of sentence pairs based on transformer encoders

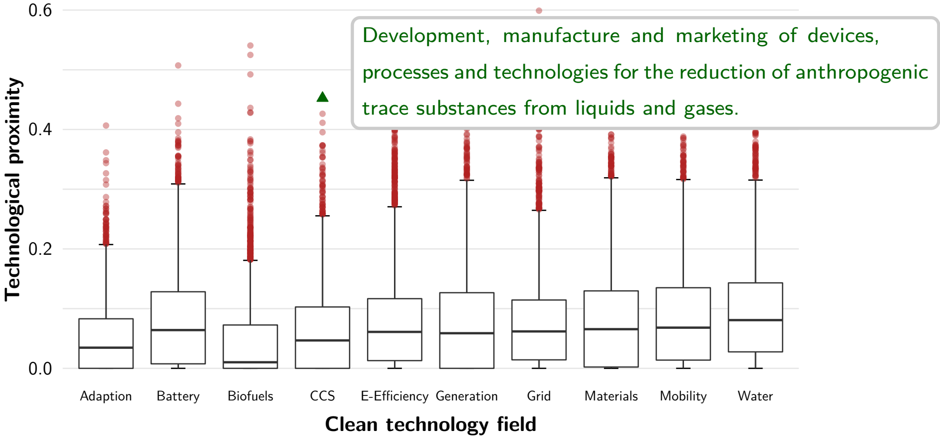
# Application

## A glance at the ‘outliers’



# Application

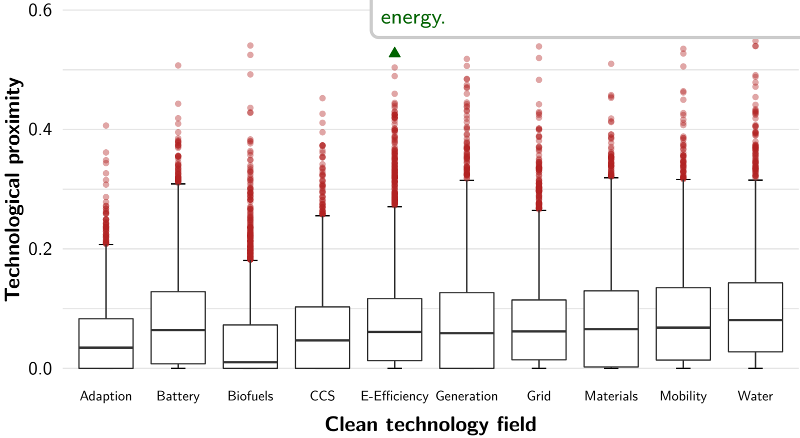
## A glance at the ‘outliers’



# Application

## A glance at the 'outliers'

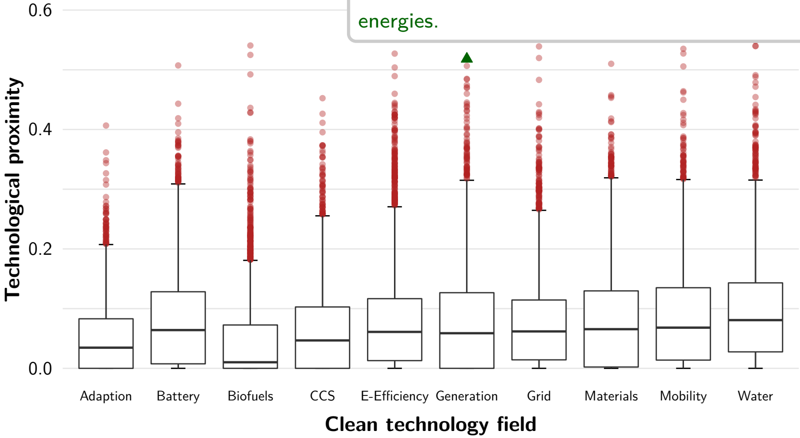
Manufacture, sale, maintenance and repair of heat pumps and other technical equipment, in particular for generating thermal energy.



# Application

## A glance at the 'outliers'

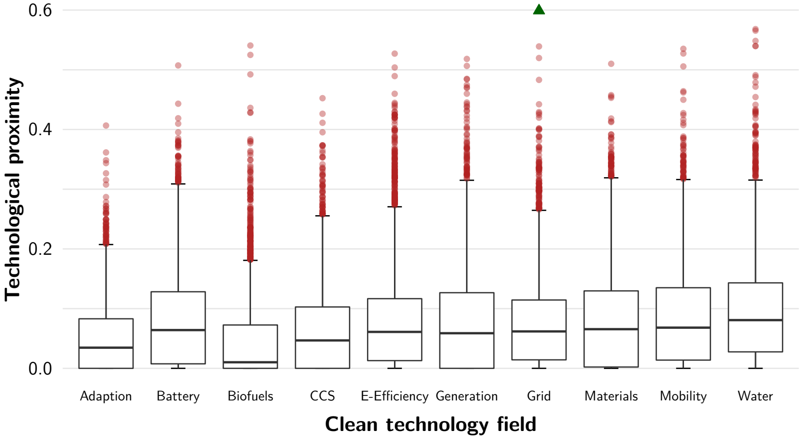
The construction, distribution and sale of turnkey photovoltaic systems and other activities of all kinds in the field of renewable energies.



# Application

## A glance at the ‘outliers’

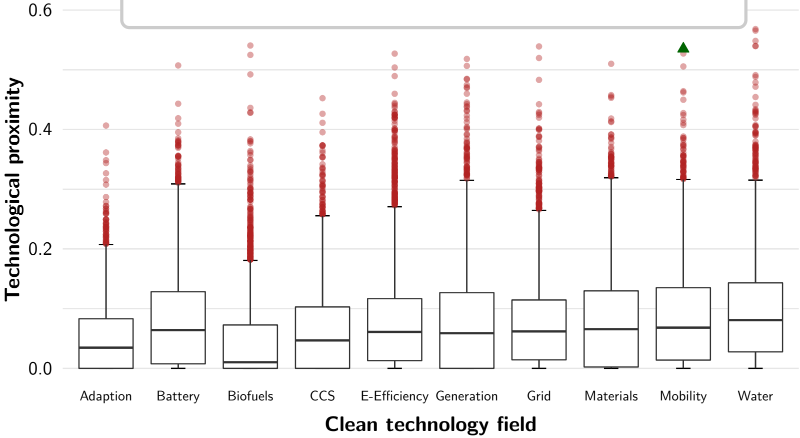
Manufacture of electrode foils, lithium accumulators and energy storage systems and the provision of services in this area.



# Application

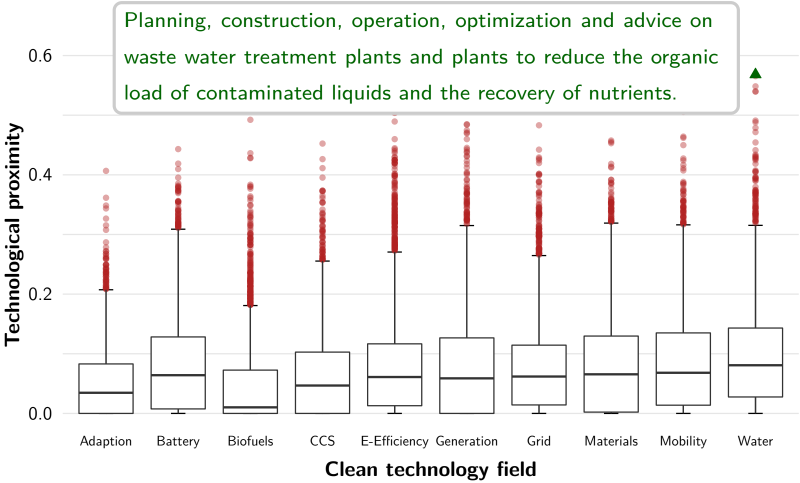
## A glance at the 'outliers'

Engine and software optimization on motor vehicles of all kinds.



# Application

## A glance at the 'outliers'



# IAB/ZEW Start-up survey

## A representative sample of German start-up companies (Gottschalk, 2013)

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.

# 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 |

*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: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$