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Predictive Modeling of Patent Quality by Using Text Mining

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Data and text mining techniques improve *predictive modeling of patent quality*

- We model "patent quality" which is a goodness measure of a patent for entire society from the predictive viewpoint
- We show data mining and text-mining techniques improve prediction
- Combining both, we further improve prediction

Background: Patent *value* is important for companies … but this is not always true for entire society

- It is important to evaluate the value of each patent to one's own business:
  - Technical value for R&D (whether it is a pioneering invention or an improvement)
  - Legal value for IP departments (whether it will be held patentable/valid)
  - Economic value for business units (whether it will bear a cash flow in the future)
- There are several attempts to model and evaluate the patent value
- However, considering a patent's value only for a particular company sometimes results in increasing social costs, and inhibiting innovations …
  - Granted patents with too broad and vague claims with few embodiments result in future litigations
  - Patent trolling: abusive practice by rights holders trying to demand excessive royalty payments to other companies

Background: Patent *quality* is goodness of a patent for *society* … but its quantitative modeling is the key

- We focus on "*quality* of a patent", a new concept which emphasizes the public nature of the patent system (contrast with the patent *value*)
- The quality of a patent is the contribution of the patent not to a company, but to the entire society
- By sharing ideas about patent quality and related data, we expect to improve the quality of patent applications and examinations
- One of the ways is to provide quantitative metrics of patent quality that can provide achievable targets shared within industries.
- But how ?

Prior work: Nagata *et al*. modeled patent quality as *legal validity*

- Nagata *et al*. considered legal validity as a proxy of patent quality
  - Patents with appropriate descriptions, claims, and examinations are robust to litigations, which will reduce social cost
- They built a regression model to explain 710 legal decisions (valid/invalid) by the IP High Court in Japan for cases of patent invalidation requests

Nagata, K, M Shima, N Ono, T Kuboyama and T Watanabe
Empirical Analysis of Japan Patent Quality
In *Proc. 17th IAMOT*, 2008

Model of patent quality score: A more valid patent x will get a higher score $f(x)$

- A patent specification $\boldsymbol{x}$ is represented as a set of features (x_1, ..., x_d)
- Each parameter corresponds to contribution of each feature to the "patent quality score", which is estimated from data

patent quality score

features of a patent $\boldsymbol{x}$

$$f(\boldsymbol{x}) = w_1 x_1 + w_2 x_2 + \ldots + w_d x_d$$

a patent

model parameters

Tailored features used by Nagata *et al.*: They defined 60 hand-made features

$$f(\mathbf{x}) = w_1\boxed{x_1}+w_2\boxed{x_2}+\ldots+w_d\boxed{x_d}$$

Action	Parameters	Definition
Applicant	Domestic_P	Number of Domestic Priorities
	Paris_P	Number of Priorities under the Paris Convention
	App_JPR	Number of Japan Patent References disclosed in a patent application by applicants
	App_FPR	Number of Foreign Patent References disclosed in a patent application by applicants
	Inventors	Number of Inventors
	Applicants	Number of Applicants
Agent	Claims	Number of Claims
	Claims_I	Number of Independent Claims
	Claims_D	Number of Dependent Claims
	Claims_C	Number of kinds of Claims Categories (e.g. "method claim" "product claim" "system claim")
	Words_AC	Number of words in All Claims (0.1 times)
	Words_TC	Number of words in Claim 1 (Top Claim)(0.1 times)
	Words_DE	Number of words in the item Detailed Explanation of invention (0.01 times)
	Words_DEEBA	Number of words in the rest except Background Art from "Words_DE" (0.01 times)
	Effects	Number of words describing "effect" in "Words_DEEBA" (e.g. "may/can" "could" "superior" "useful" "advantageous")
	Arguments	Number of filing arguments
	Amendments	Number of filing amendments
	Request_OI	Number of requests for oral Interview with examiner
Examiner	Exa_JPR	Number of Japan Patent References cited by the examiner
	Exa_FPR	Number of Foreign Patent References cited by the examiner
	Exa_NPR	Number of Non Patent References cited by the examiner
	Exa_AJPR	Number of Japan Patent References added by the examiner
	Exa_AFPR	Number of Foreign Patent References added by the examiner

invoking claim of priority

number of effect words (e.g. "can")

number of cited foreign patents

Our goal: *Predictive* modeling of patent quality

- Nagata *et al.* focused on *descriptive* modeling
  - *"Which feature is responsible for explaining court decisions (=patent quality) ?"*
- To be used as a reliable quality measure, the model should have high predictive power
  - Also useful for selecting patents to file or hold
- Our goal is to improve the predictive power of the patent quality model

Results: We improved the patent quality prediction model by using *data mining* and *text mining* techniques

- Data mining techniques for prediction:
  - *Support vector machines* (*SVMs*) for accurate predictive modeling
  - *Class-proportionate weighting* for addressing biased data
- Text mining techniques for exhaustive text feature construction from patent specifications
  - *Morphological analysis* for natural language processing
  - *L1-regularization* for addressing high-dimensional data
- Furthermore, combination of both boosts the predictive power

Key for improvement 1: Use *all* features

- Nagata *et al*. selected 24 promising features out of 60 features, but can we improve the predictive accuracy by using all of them ?
- In data mining, it is common to use all features by using the framework called regularization
  - Regularization prevents model parameters ($w_1, w_2, \ldots, w_d$) from being too large or too small

$$f(\boldsymbol{x}) = w_1 x_1 + w_2 x_2 + \ldots + w_d x_d$$

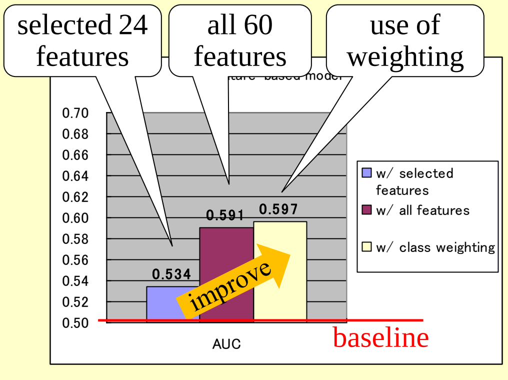
    - by penalizing $\|w\|_2^2 := w_1^2 + w_2^2 + \ldots + w_d^2$
- We use support vector machine, which is a state-of-the-art prediction model used in data mining

Key for improvement 2: Address the *bias* in the data

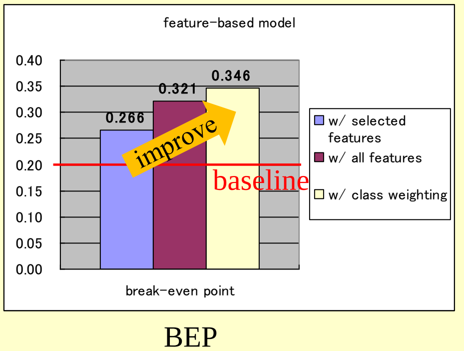
- Valid patents make up only 20% of the whole data
  - Invalid cases are 80%/20% = 4 times as many as valid cases
- Can we use this bias information to improve estimation ?
- Intuitively, it sounds nice to put more importance on valid cases (=minorities)
  - Class proportionate weighting: Estimates the model by giving 4 times as large weights to valid cases as those to invalid cases
    - known to improve predictive performance

Result 1&2: Data mining techniques improve prediction !

- Using support vector machine, the predictive performance improves
  - when we use all 60 features
  - when we use class-proportionate weighting



AUC



BEP

Key for improvement 3: Use *text* information

- In patent specifications, we have rich text information
- We use text mining techniques to exhaustively construct features from texts
  - *Morphological analyzer* to segment Japanese language into words

醸造に要する時間を大幅に短縮することができる
we can significantly shorten the time for brewing

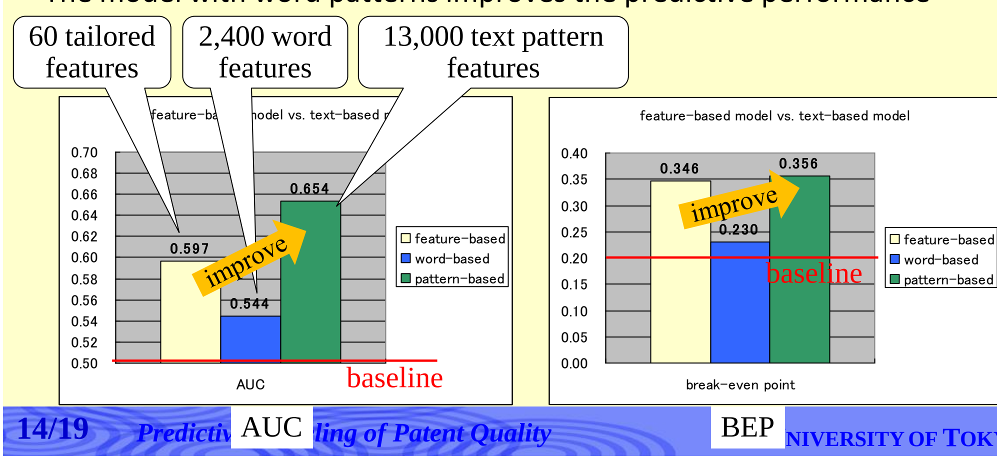
⇩

醸造 | に | 要する | 時間 | を | 大幅 | に | 短縮 | する | こと | が | できる
[noun] [particle] [verb] [noun] [particle] [noun] [particle] [noun] [verb] [noun] [particle] [verb]

  - Combining words to extract 13,000 patterns consisting of 2 or 3 words
- *L1-regularization* for addressing high-dimensional data (#features >> #data)
  - L1-regularization dramatically and automatically reduces the number of features used in the model (then we got about 100 selected features)
    - by penalizing $|w|_1 := |w_1| + |w_2| + \ldots + |w_d|$

Result 3.1: Text information improves prediction !

- We built two models:
  - The model with 2,400 words
  - The model with 13,000 patterns consisting of 2- or 3-consecutive-word patterns
- The model with word patterns improves the predictive performance



Result 3.2:
We found textual patterns implying high patent quality

- Investigating the model, we found informative text representations:
  - Textual patterns clarifying or limiting coverage of claims
  - Textual patterns representing effects of patent executions
    - This is consistent with the mention by Nagata *et al.*

clarifying or limiting coverage of claims

interpretations	patterns (in Japanese)	meanings of the patterns
parameters	度合い[noun]-を[particle]	degree of …
	確率[noun]-の[particle]	probability of …
	の[particle]-設定[noun]	setting of …
extension of existing patents	(実施)形態[noun]-による[particle], で[particle]-用い[verb]-て[particle]	executed in the condition of …
	に[particle]-置き換え[verb]	substitute … with …
	薄型[noun]-化[noun]	reduce the thickness of …
effect representations	を[particle]-良く[adjective]	well
	正しい[adjective]	correct
	可撓性[noun]	flexibility
	利点[noun], 利点[noun]-を[particle]	advantage
	調整[noun]-可能[noun]	adjustable

Key for improvement 4:
Combine tailored-feature-based model and text-based model

- Can we further improve the prediction by combining the 1st (tailored-feature-based) model and the 2nd (text-based) model
- Two ways of combining two models:
  - Collaborative model: sums the outputs by two models

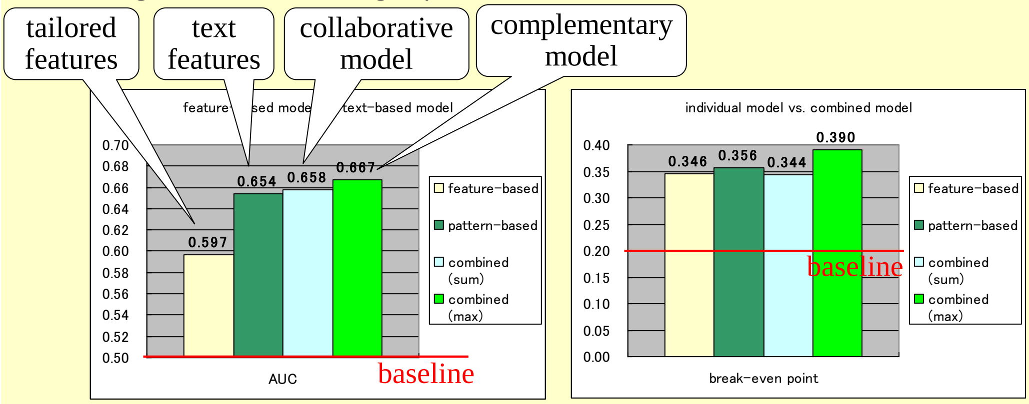
$$f^{tailored}(x) + f^{text}(x)$$

  - Complementary model: takes the maximum of the two models

$$\max\{ f^{tailored}(x), f^{text}(x) \}$$

Result 4: Two models work complementarily to improve prediction

- Complementary model (taking the max.) works well
- This means that two models work complementarily
  - "Right model in the right place"



AUC BEP

Conclusion: *Data and text mining* techniques improve *predictive modeling of patent quality*

- We modeled not "patent value " for a specific company, but "patent quality" for entire society, from the predictive viewpoint
- We showed data mining techniques improve prediction (1, 2)
- Using text mining techniques,
  we showed texts are informative for patent quality modeling (3)
- Hand-made features and text-based features work complementarily to improve prediction (4)
- Future work includes:
  - More precise modeling using large scale data
  - Modeling with other proxies of patent quality (e.g. patentability)

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- Kentaro Nagata

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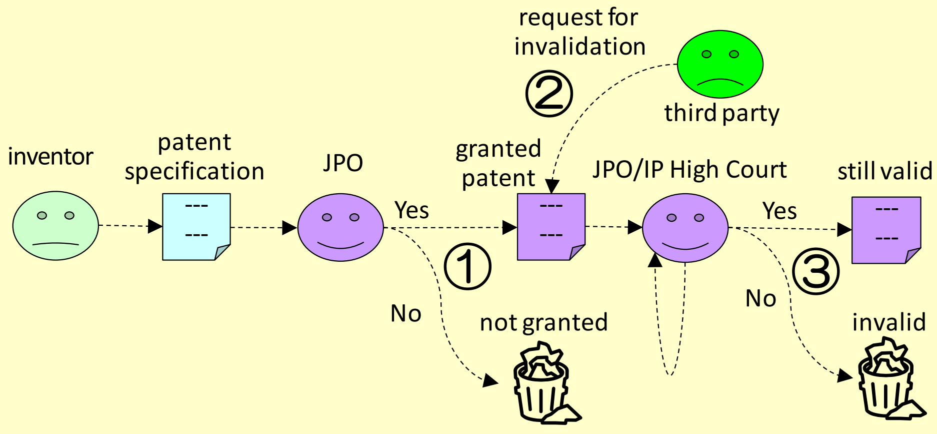
Backup

Simplified flowchart of the patenting system in Japan

- Nagata *et al.* focused on modeling (3)

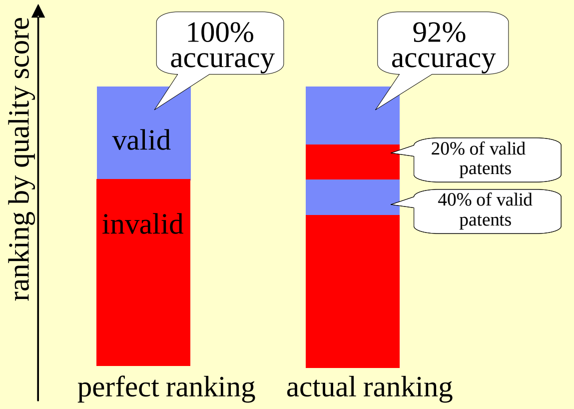


Evaluation method of predictive accuracy: *Cross validation* and two predictive performance metrics (*AUC* & *BEP*)

- Cross validation allows us to virtually evaluate predictive performance on future cases
  - Use 80% of the data for modeling
  - Use the remaining 20% for evaluation (with court decisions hidden)
- 2 widely-used predictive performance metrics: AUC and BEP
  - AUC (Area Under the ROC Curve):
    - Evaluates the quality of ordering of predictions
    - Equivalent to AR(Accuracy Rate)-value used as a performance metric for default prediction in financial engineering
  - BEP (Break-Even Point):
    - Evaluate accuracy rate with an optimal decision threshold
    - Used for evaluating quality of automatic text classification

AUC: a measure of ranking quality

- The patents in the evaluation set are ordered by using the model
- AUC is probability of a randomly-picked stable patent ranked higher than a randomly-picked instable patent
- AUC is a measure of quality of *ranking*



Break-even point: a measure of predictive accuracy with threshold

- The patents in the evaluation set are ordered by using the model
- Top *N* instances are predicted as "stable", where *N* is the number of stable patents in the evaluation set
  - because this is the optimal decision threshold if the model is correct
- Break even point is predictive accuracy for the instances given "stable" labels by using the optimal threshold