Neural Ideal Point Estimation Network (NIPEN)

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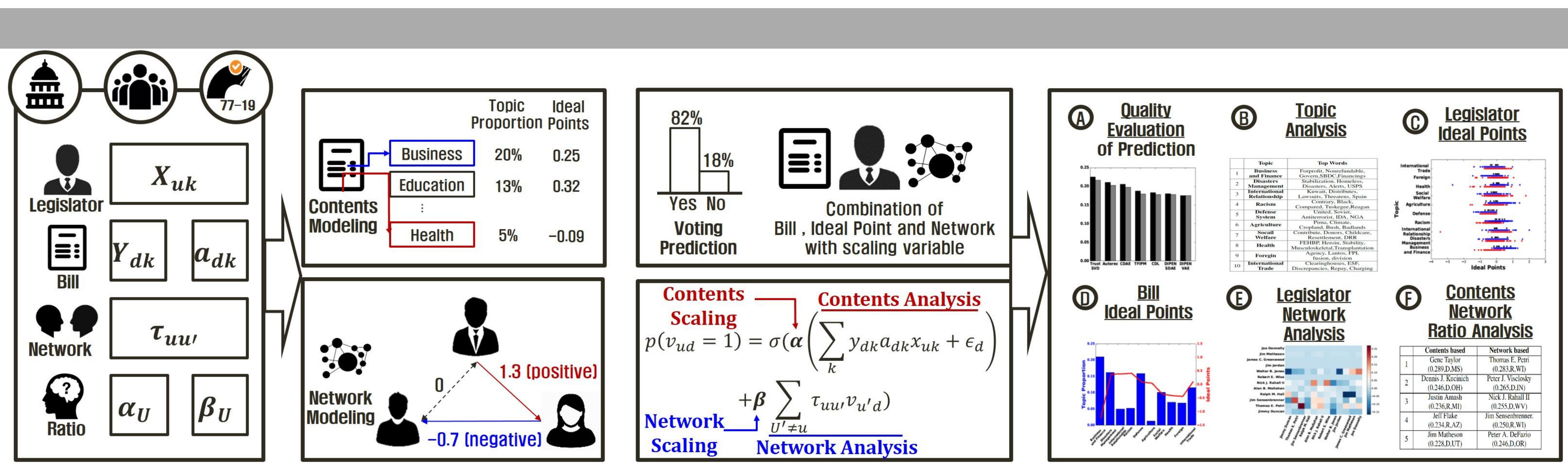
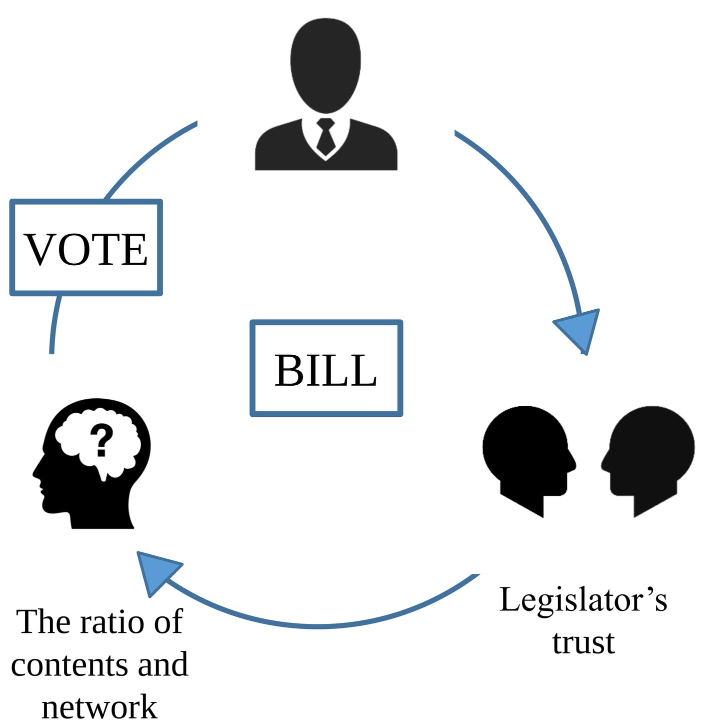
Why did legislator "X" vote on bill "Y" as "YEA"? (Interpretable Model)



Motivation

- Political ideal points are expressed by legislative voting
- Political ideal points affects public behavior patterns
- It is necessary to understand the Congressional votes

Research Questions



- RQ 1) Quantifying the ideal points of bills / legislators
- RQ 2) Quantification of trust between legislators
- RQ 3) Modeling the behavior of individual legislators, taking into account ideal points and trust
- RQ 4) Voting predictions for individual legislators

Modeling Assumption

The modeling assumption of NIPEN is based on the theory claimed in the political domain.

- Ideal point is important in the legislative process (Poole and Rosenthal, AJPS 1991)
- Multi-dimensional representation of the ideal point is necessary (Clinton, APSR 2010)
- The legislative process must be influenced by the social network between the legislators (Kirkland, The journal of politics 2011)
- Relation could be asymmetric (Fowler, APSA 2005)
- the voting is relevant to the ideal point as well as the network (Jackson, AJPS 1992)

Dataset

- Roll call data : The recorded votes of deliberative bodies
- Politic2013 and Politic2016 include records 1990~2013 and 1990~2016 respectively
- Politic2013 is a more sparse dataset than Politic2016 in the ratings and the vocabulary sizes.

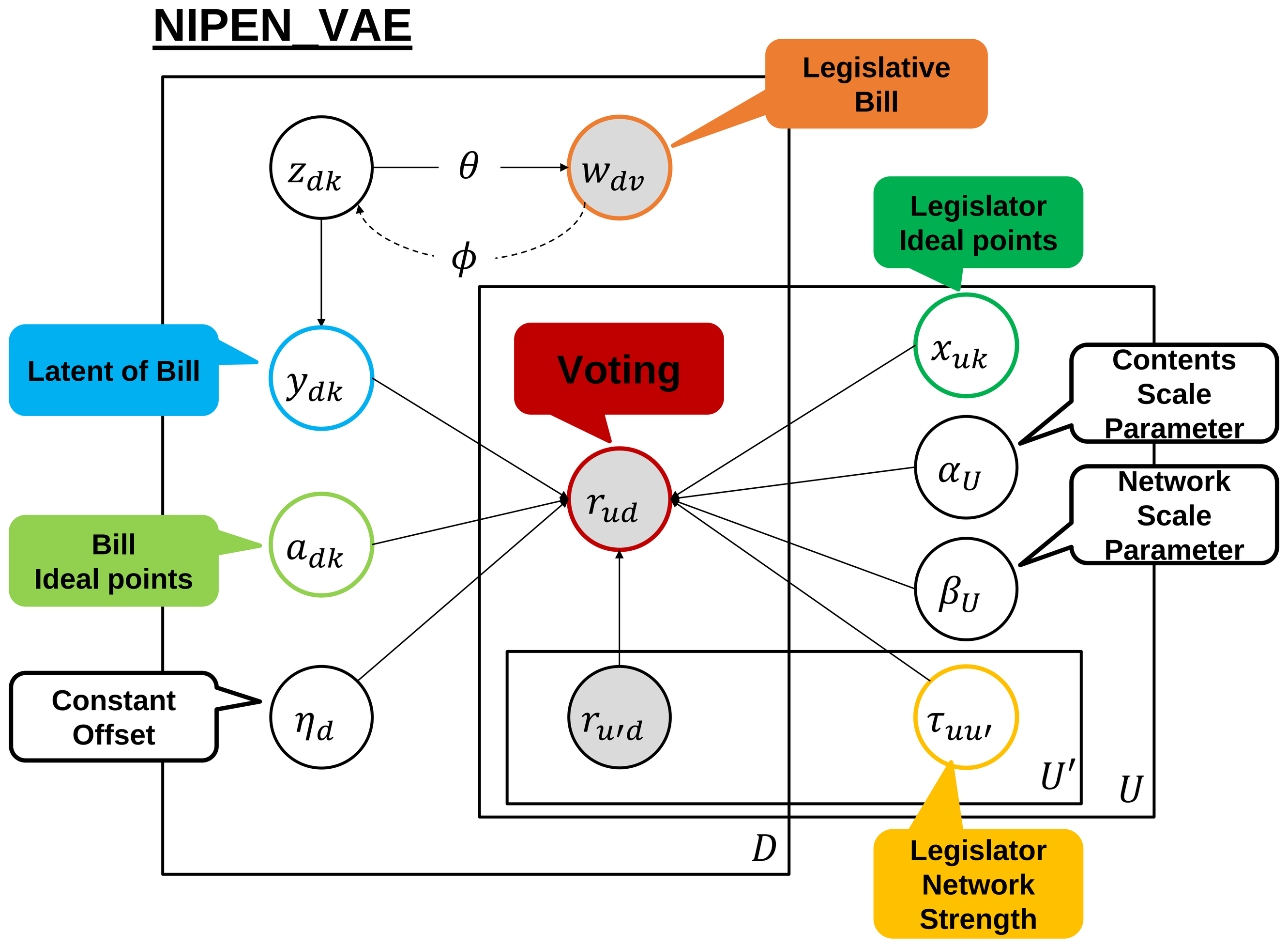
	Politic2013	*Politic2016*
# of legislators ($\lvert U \rvert$)	1,540	1,537
# of bills ($\lvert D \rvert$)	7,162	7,975
# of votings ($\lvert D \rvert$)	2,779,703	2,999,844
# of House	1,299	1,266
# of Senator	241	271
# of Republican	767	778
# of Democrat	767	752
# of unique word ($\lvert V \rvert$)	10,000	13,581
Average # of unique word for each bill ($\frac{\sum_{d,v}(I_{w_{dv}>0})}{V}$)	192.77	378.66
# of bills less than 10 unique words	65	0
Period	1990-2013	1989-2016
Source	THOMAS	GovTrack
Data type	1 (YEA), -1 (NAY)	

Politic2013 : Thomas [Yupeng Gu, 2014] / Politic2016 : Govtrack

Methodology

- We adopted VAE / SDAE to model the bills and combined it with various causalities to create a model with high explanatory power
- In order to consider the correlation between the topics in the bills, we adopted a tensor-based operation
- NIPEN-Tensor is a more generalized model than the existing models (including NIPEN-VAE/SDAE).

NIPEN_VAE



VAE for bill modeling :

- $L = -D_{KL}(q_\phi(z|w)||p_\theta(z)) + \frac{1}{L}\sum_{l=1}^{L}\log p_\theta(w|z^l)$

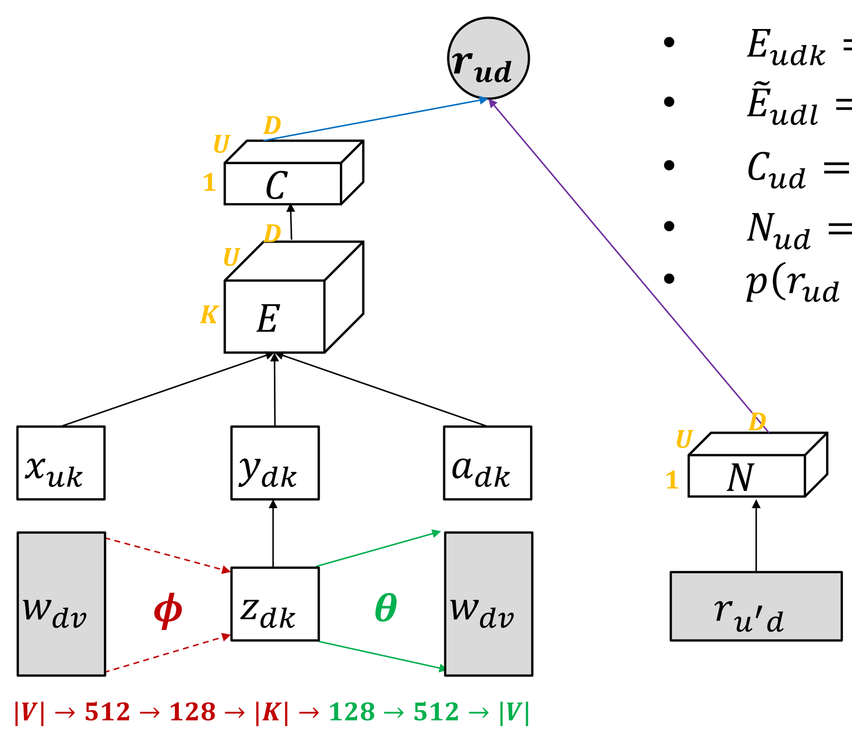
Voting modeling with contents and network component :

- $p(r_{ud} = 1) = \sigma(\alpha_u \underbrace{(\sum_k y_{dk}a_{dk}x_{uk} + \eta_d)}_{= C_{ud}} + \beta_u \underbrace{(\sum_{u' \in I_u} \tau_{uu'} r_{u'd})}_{= N_{ud}})$

Assumption :

- $a_{dk}x_{uk} > 0$ and $y_{dk} \uparrow \Rightarrow p(r_{ud} = 1) \uparrow$
- $\tau_{uu'} \uparrow$ and $r'_{ud} = 1 \Rightarrow p(r_{ud} = 1) \uparrow$
- $C_{ud}, N_{ud} > 0$ and $\alpha_u, \beta_U \uparrow \Rightarrow p(r_{ud} = 1) \uparrow$

NIPEN_Tensor

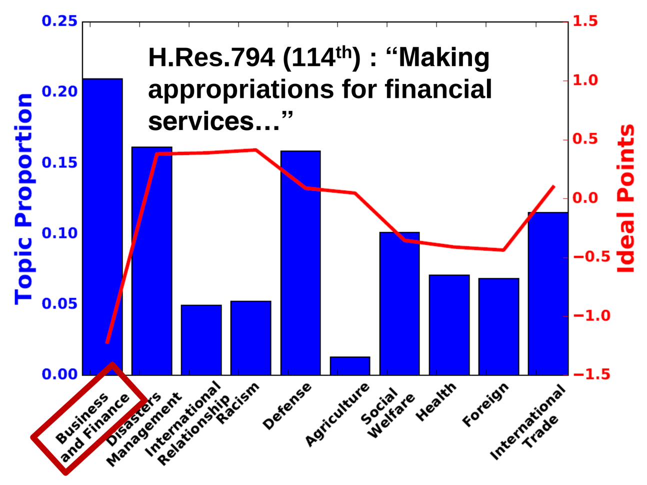


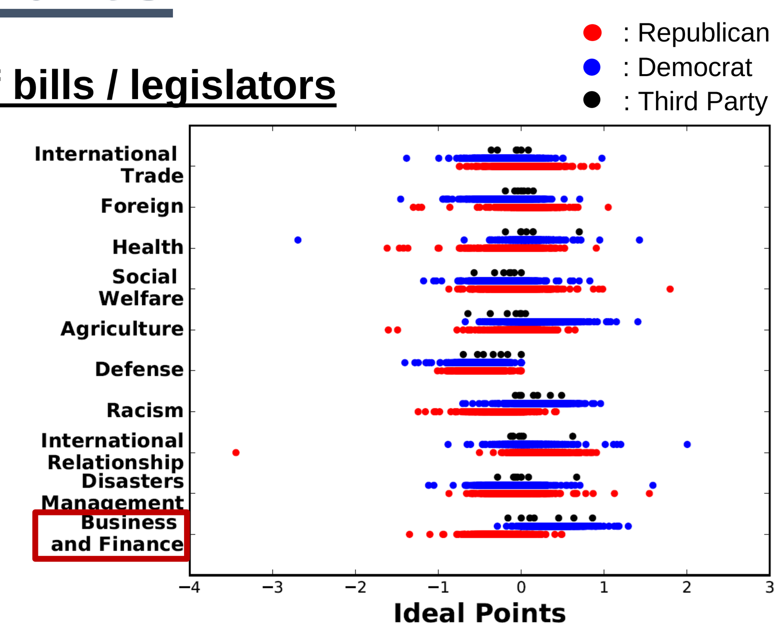
- $E_{udk} = x_{uk}y_{dk}z_{dk}$
- $\tilde{E}_{udl} = \sum_k E_{udk}W_{kl}^{(T_1)} + b_l^{(T_1)}$
- $C_{ud} = \sum_l \tilde{E}_{udl}W_{l1}^{(T_2)} + \eta_d$
- $N_{ud} = \sum_{u' \in U} \tau_{uu'}v_{u'd}$
- $p(r_{ud} = 1) = \sigma(\alpha_u C_{ud} + \beta\Sigma_{u' \in I_u} N_{u'd})$

- If multiple topics are combined, the ideal point for that topic combination may vary.
- Existing models derive an ideal points for cross-topic by simple summation.
- **NIPEN-Tensor to incorporate the cross-topic influence in casting a vote, and it is a generalized version of existing model**

Results

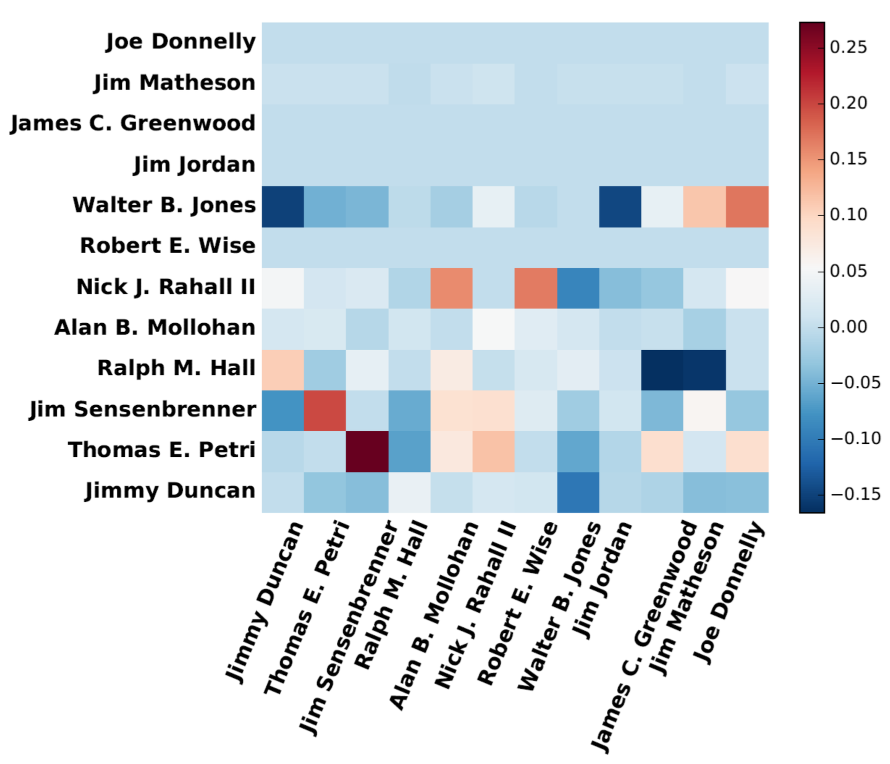
RQ 1) Quantifying the ideal points of bills / legislators

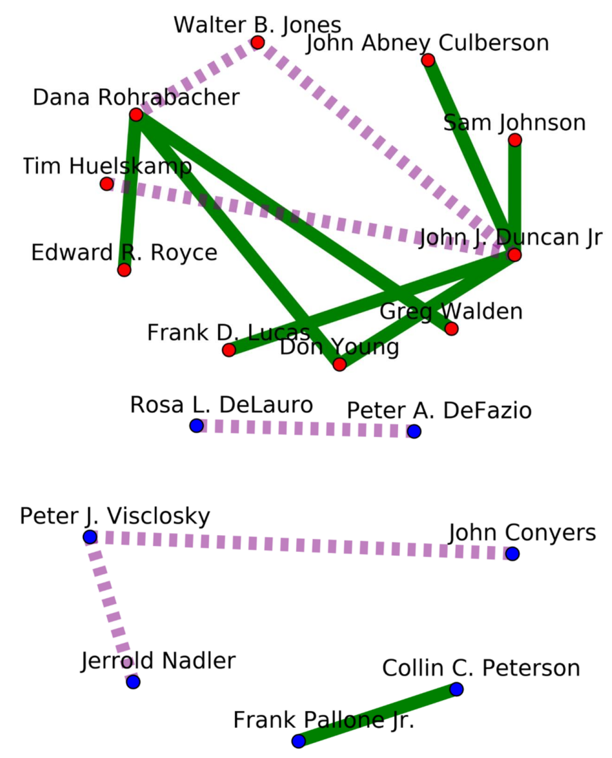




- The major topic of H.Res.794 (114th) is "Business and Finance" with negative ideal points
- There is greatest disagreement between the Republicans and the Democrats on that topic
- The voting was very partisan (92.2% republican voted YEA and 90.3% Democrat voted NAY)

RQ 2) Quantification of trust between legislators

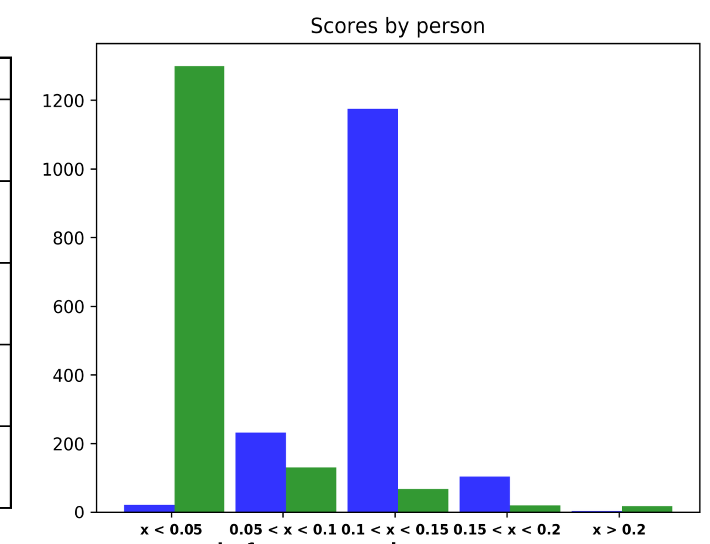




- In general, the legislators have a strong positive relationship when they have the same district and the party
- The closest relation is 'Thomas E. Petri' and 'Jim Sensenbrenner'. (Republican representatives from Wisconsin)
- J. Duncan Jr and Dana Rohrabacher have the greatest network impact on the Republican party. (Duncan started as a congressman in Tennessee in 1988 and Rohrabacher as a California congressman in 1989.)

RQ 3) Modeling the behavior of individual legislators, taking into account ideal points and trust

	Contents based	Network based
1	Ron Paul (0.260, R, TX)	Ralph M. Hall (0.304, R, TX)
2	Virgil H. Goode (0.220, R, VA)	Nick J. Rahall II (0.250, D, WV)
3	Dennis J. Kucinich (0.218, D, OH)	Peter A. DeFazio (0.247, D, OR)
4	Henry Cuellar (0.198, D, TX)	Don Young (0.228, R, AK)
5	Walter B. Jones (0.195, R, NC)	Jim Sensenbrenner. (0.227, R, WI)



- Top-five legislators who are affected by contents or network factors a lot
- Majority of legislators are voting to focus on contents rather than network effect
- A small number of legislators are highly dependent on the network effect.

RQ 4) Voting predictions for individual legislators

	Politic2013				*Politic2016*			
	RMSE	MAE	Accuracy	NALL	RMSE	MAE	Accuracy	NALL
Trust SVD	0.2253 (±0.0007)	0.1399 (±0.0011)	0.9408 (±0.0003)	0.1866 (±0.0011)	0.2168 (±0.0011)	0.1353 (±0.0010)	0.9463 (±0.0009)	0.1782 (±0.0015)
Autorec	0.2110 (±0.0099)	0.0975 (±0.0136)	0.9411 (±0.0056)	0.1466 (±0.0177)	0.2031 (±0.0015)	0.0886 (±0.0110)	0.9454 (±0.0007)	0.1349 (±0.0125)
CDAE	0.2059 (±0.0007)	0.0831 (±0.0009)	0.9428 (±0.0006)	0.1450 (±0.0009)	0.1977 (±0.0037)	0.0802 (±0.0052)	0.9475 (±0.0023)	0.1357 (±0.0046)
TFIPM	0.1872 (±0.0002)	0.0682† (±0.0002)	0.9526 (±0.0003)	0.1213 (±0.0007)	0.1794 (±0.0010)	0.0625† (±0.0006)	0.9566 (±0.0005)	0.1121 (±0.0016)
CDL	0.1834† (±0.0008)	0.0786 (±0.0019)	0.9554† (±0.0004)	0.1147† (±0.0018)	0.1780† (±0.0013)	0.0769 (±0.0012)	0.9583† (±0.0008)	0.1106† (±0.0017)
NIPEN-PGM(SDAE)	0.1801** (±0.0014)	0.0591** (±0.0012)	0.9566** (±0.0006)	0.1155 (±0.0018)	0.1779 (±0.0005)	**0.0560**** (±0.0004)	0.9581 (±0.0003)	0.1173 (±0.0015)
NIPEN-PGM(VAE, approx.)	0.1804 (±0.0089)	0.0611* (±0.0065)	0.9565 (±0.0047)	0.1165 (±0.0086)	0.1791 (±0.0076)	0.0599 (±0.0057)	0.9571 (±0.0039)	0.1152 (±0.0070)
NIPEN-PGM(VAE)	**0.1753**** (±0.0007)	**0.0588**** (±0.0008)	**0.9587**** (±0.0006)	**0.1075**** (±0.0011)	0.1753** (±0.0017)	0.0570** (±0.0012)	0.9590** (±0.0010)	0.1112 (±0.0024)
NIPEN-Tensor	0.1818** (±0.0008)	0.0663** (±0.0003)	0.9556** (±0.0003)	0.1155 (±0.0020)	**0.1729**** (±0.0015)	0.0608** (±0.0006)	**0.9600**** (±0.0008)	**0.1057**** (±0.0022)
Improvement	4.41%	13.78%	0.35%	6.27%	2.87%	10.40%	0.18%	4.43%

NALL : Negative Average Log Likelihood
Improvement : Relative improvement of the best version of NIPEN compared to the best model, which is marked by †, among the baselines
$P^* < 0.05$; $P^{**} < 0.01$ (Student's one-tailed t-test against the † model)

- **Variations of NIPEN shows the best performance in every metric and dataset**
- NIPEN-Tensor is a model that considers the correlation between topics, and NIPEN-Tensor may have a better performance when a bill text has multiple topics with complex and rich textual information