Journey of Keyphrase Extraction

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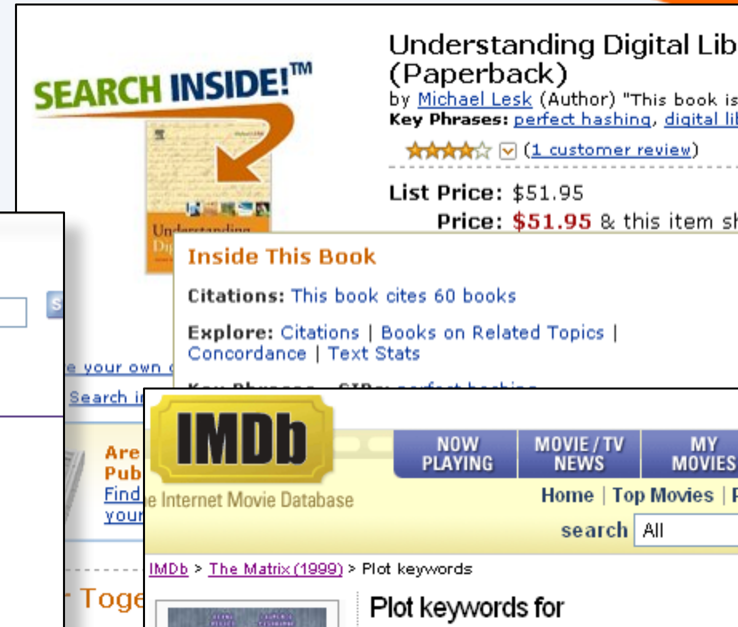
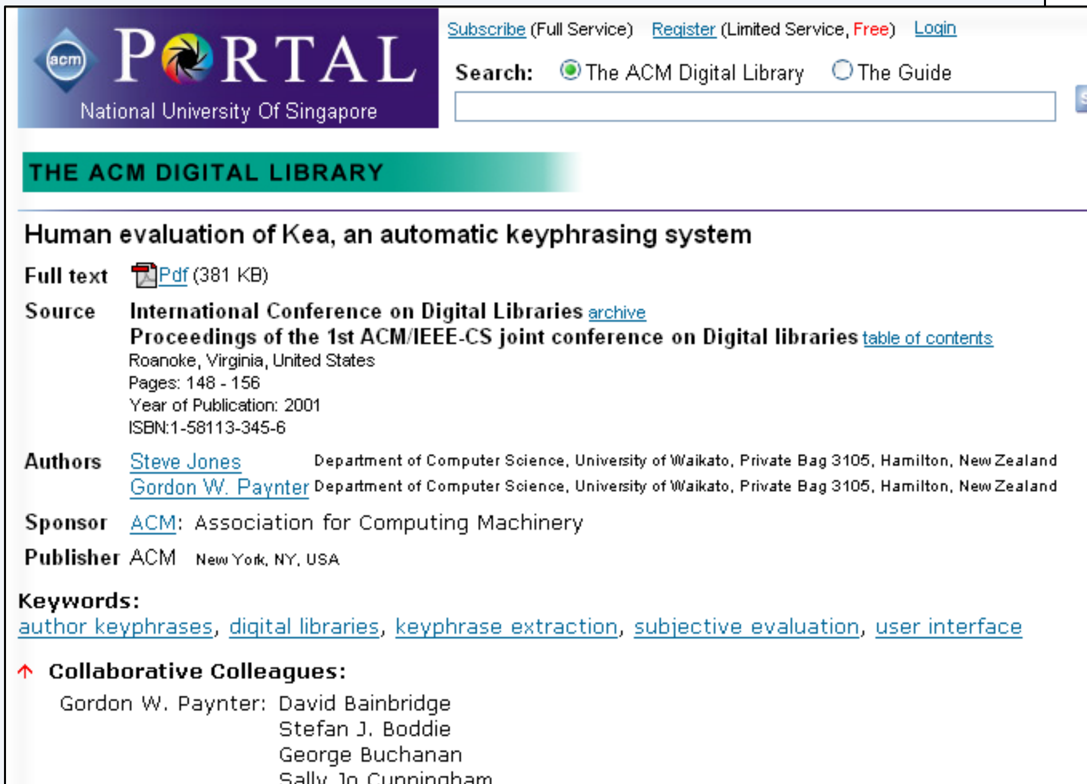
DSO Data Science & AI Talk Series
Nov 2, 2017

What is Keyphrase Extraction?

Key Concept 1
Key Concept 2
....

Keyphrases everywhere!





*To think about: Are **tags** keyphrases?*

Credits: Amazon.com, ACM.org, IMDB.com

Why do we care?

- information retrieval (IR) tasks,
  - such as text summarization,
  - text categorization,
  - opinion mining and
  - document indexing

Corpora

Source	Dataset/Contributor	Statistics		
		Documents	Tokens/doc	Keys/doc
Paper abstracts	*Inspec* [20] ∗	2,000	< 200	10
Scientific papers	NUS corpus [42] ∗	211	≈ 8K	11
	citeulike.org [37] ∗	180	-	5
	SemEval-2010 [27] ∗	284	> 5K	15
Technical reports	NZDL [56] ∗	1,800	-	-
News articles	DUC-2001 [53] ∗	308	≈ 900	8
	Reuters corpus [19]	12,848	-	6
Web pages	Yih et al. (2006)	828	-	-
	Hammouda et al. (2005) ∗	312	≈ 500	-
	Blogs [13]	252	≈ 1K	8
Meeting transcripts	ICSI [30]	161	≈ 1.6K	4
Emails	Enron corpus [9] ∗	14,659	-	-
Live chats	Library of Congress [25]	15	-	10

Apporaches

KEA 1999

- Supervised
  - Binary Classification
    - naïve Bayes,
    - decision trees,
    - bagging,
    - boosting,
    - maximum entropy,
    - multi-layer perceptron,
    - and support vector machines

Apporaches

KEA —— 1999

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    - maximum entropy,
    - multi-layer perceptron,
    - and support vector machines
  - Problem? Classification is not a tournament!

Apporaches

- Supervised
  - Binary Classification
  - Problem? Classification is not a tournament!
  - Ranking

KEA 1999

Jiang et al 2009

Apporaches

- Supervised
  - Features
    - In document features
      - Statistical features

        tf-idf, keyphraseness etc
      - Structural features

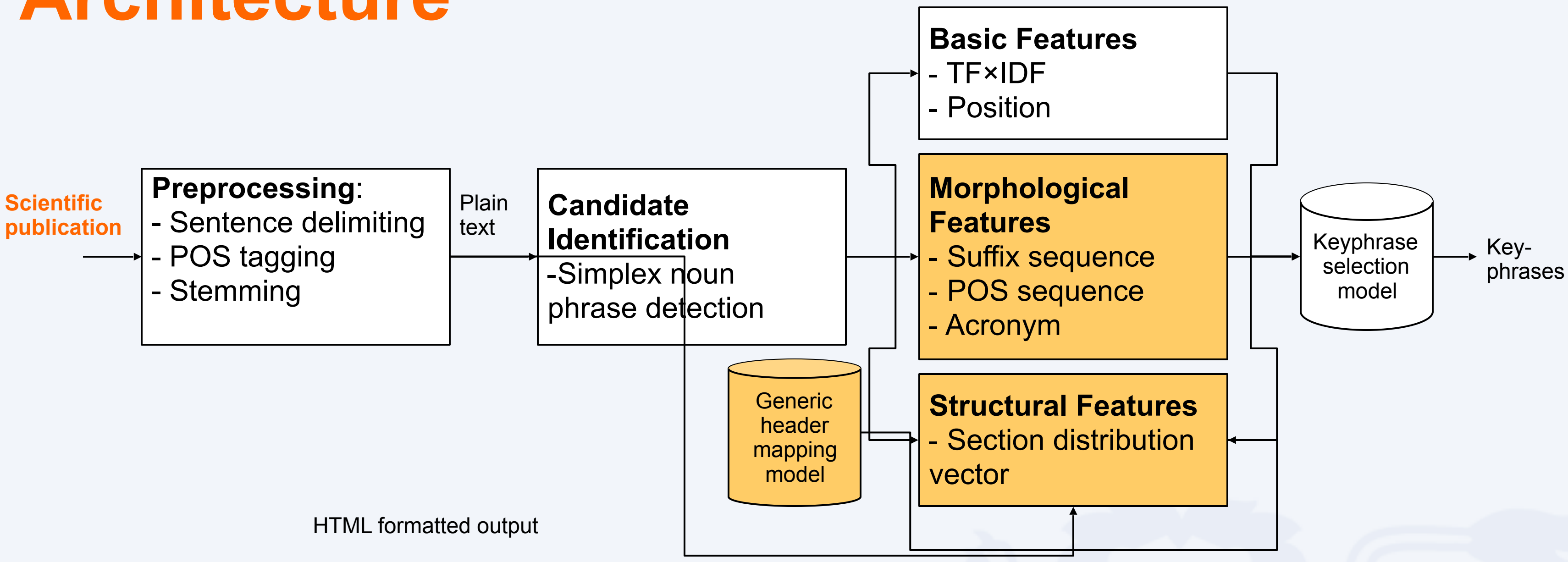
        document structure like section etc
      - Syntactic features

        POS tags etc

Apporaches

- Supervised
  - Features
    - In document features
    - Out of the document features
      - Wikipedia-based keyphraseness
      - Search Log based keyphraseness
      - *Web as a corpus for related terms*

Architecture



Apporaches

- Unsupervised
  - Graph-Based Ranking
    - TextRank (Page Rank)
  - Clustering with Wikipedia
  - Topical PageRank

  - And many more complex graph based algorithm

Text Rank 2004

Liu et al 2010

Benchmarking

- Unsupervised
  - Graph-Based Ranking
    - TextRank (Page Rank)
  - Clustering with Wikipedia
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  - Any many more complex graph based algorithm

Benchmarking

Dataset	Author	Reader	Combined
Trial	149	526	621
Training	559	1824	2223
Test	387	1217	1482

SemEval 2010

Benchmarking

System	Rank	Top 5 candidates			Top 10 candidates			Top 15 candidates		
		P	R	F	P	R	F	P	R	F
HUMB	1	39.0%	13.3%	19.8%	32.0%	21.8%	26.0%	27.2%	27.8%	27.5%
WINGNUS	2	40.2%	13.7%	20.5%	30.5%	20.8%	24.7%	24.9%	25.5%	25.2%
KP-Miner	3	36.0%	12.3%	18.3%	28.6%	19.5%	23.2%	24.9%	25.5%	25.2%
SZTERGAK	4	34.2%	11.7%	17.4%	28.5%	19.4%	23.1%	24.8%	25.4%	25.1%
ICL	5	34.4%	11.7%	17.5%	29.2%	19.9%	23.7%	24.6%	25.2%	24.9%
SEERLAB	6	39.0%	13.3%	19.8%	29.7%	20.3%	24.1%	24.1%	24.6%	24.3%
KX_FBK	7	34.2%	11.7%	17.4%	27.0%	18.4%	21.9%	23.6%	24.2%	23.9%
DERIUNLP	8	27.4%	9.4%	13.9%	23.0%	15.7%	18.7%	22.0%	22.5%	22.3%
Maui	9	35.0%	11.9%	17.8%	25.2%	17.2%	20.4%	20.3%	20.8%	20.6%
DFKI	10	29.2%	10.0%	14.9%	23.3%	15.9%	18.9%	20.3%	20.7%	20.5%
BUAP	11	13.6%	4.6%	6.9%	17.6%	12.0%	14.3%	19.0%	19.4%	19.2%
SJTULTLAB	12	30.2%	10.3%	15.4%	22.7%	15.5%	18.4%	18.4%	18.8%	18.6%
UNICE	13	27.4%	9.4%	13.9%	22.4%	15.3%	18.2%	18.3%	18.8%	18.5%
UNPMC	14	18.0%	6.1%	9.2%	19.0%	13.0%	15.4%	18.1%	18.6%	18.3%
JU_CSE	15	28.4%	9.7%	14.5%	21.5%	14.7%	17.4%	17.8%	18.2%	18.0%
LIKEY	16	29.2%	10.0%	14.9%	21.1%	14.4%	17.1%	16.3%	16.7%	16.5%
UvT	17	24.8%	8.5%	12.6%	18.6%	12.7%	15.1%	14.6%	14.9%	14.8%
POLYU	18	15.6%	5.3%	7.9%	14.6%	10.0%	11.8%	13.9%	14.2%	14.0%
UKP	19	9.4%	3.2%	4.8%	5.9%	4.0%	4.8%	5.3%	5.4%	5.3%

Benchmarking

Unsupervised

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Shift in Focus

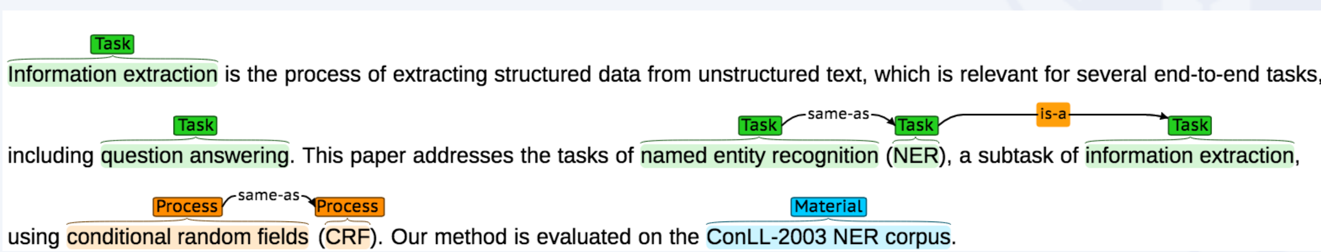
- Tens of work on incorporating domain specific, semantically rich feature for extraction algorithm
- Meanwhile DARPA's MUC7 saw approx. 88% results and leading to subsequent research in KB using entities
- This lead to shift in focus for keyphrases from indexing component to an upstream task for KBC

SemEval 2017

Shift in Focus

- **Named Entity Recognition**

- **SemEval 2017 Keyphrase Extraction**



SemEval 2017

Benchmarking SemEval 2017 Task 10: Science IE

- **Subtask (A): Identification of keyphrases**
- Given a scientific publication, the goal of this task is to identify all the keyphrases in the document.

- **Subtask (B): Classification of identified keyphrases**
- In this task, each keyphrase needs to be labelled by one of three types: (i) PROCESS, (ii) TASK, and (iii) MATERIAL.
- PROCESS: Keyphrases relating to some scientific model, algorithm or process should be labelled by PROCESS.
- TASK: Keyphrases those denote the application, end goal, problem, task should be labelled by TASK.
- MATERIAL: MATERIAL keyphrases identify the resources used in the paper.

- **Subtask (C): Extraction of relationships between two identified keyphrases**
- Every pair of keyphrases need to be labelled by one of three types: (i) HYPONYM-OF, (ii) SYNONYM-OF, and (iii) NONE.
- HYPONYM-OF: The realtionship between two keyphrases A and B is HYPONYM-OF if semantic field of A is included within that of B. One example is Red HYPONYM-OF Color.
- SYNONYM-OF:The realtionship between two keyphrases A and B is SYNONYM-OF if they both denote the same semantic field, for example Machine Learning SYNONYM-OF ML.

Benchmarking SemEval 2017 Task 10: Science IE

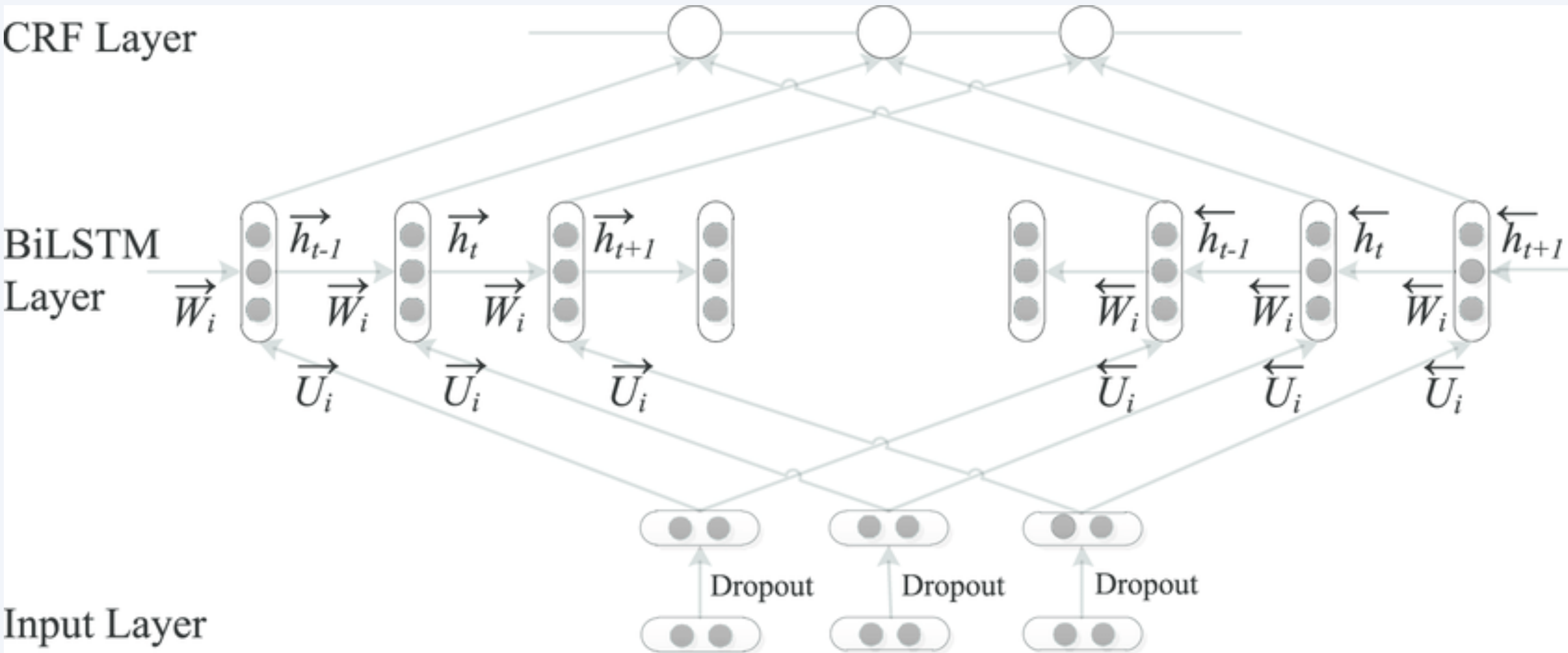
Teams	Overall	A	B	C
s2_end2end (Ammar et al., 2017)	**0.43**	0.55	**0.44**	**0.28**
TIAL_UW	0.42	**0.56**	**0.44**	
TTI_COIN (Tsujimura et al., 2017)	0.38	0.5	0.39	0.21
PKU_ICL (Wang and Li, 2017)	0.37	0.51	0.38	0.19
NTNU-1 (Marsi et al., 2017)	0.33	0.47	0.34	0.2
WING-NUS (Prasad and Kan, 2017)	0.27	0.46	0.33	0.04
Know-Center (Kern et al., 2017)	0.27	0.39	0.28	
SZTE-NLP (Berend, 2017)	0.26	0.35	0.28	
NTNU (Lee et al., 2017b)	0.23	0.3	0.24	0.08
LABDA (Segura-Bedmar et al., 2017)	0.23	0.33	0.23	
LIPN (Hernandez et al., 2017)	0.21	0.38	0.21	0.05
SciX	0.2	0.42	0.21	
IHS-RD-BELARUS	0.19	0.41	0.19	
HCC-NLP	0.16	0.24	0.16	
NITK_IT_PG	0.14	0.3	0.15	
Surukam	0.1	0.24	0.1	0.13
GMBUAP (Flores et al., 2017)	0.04	0.08	0.04	
upper bound	0.84	0.85	0.85	0.77
random	0.00	0.03	0.01	0.00

BiLSTM CRF Benchmark

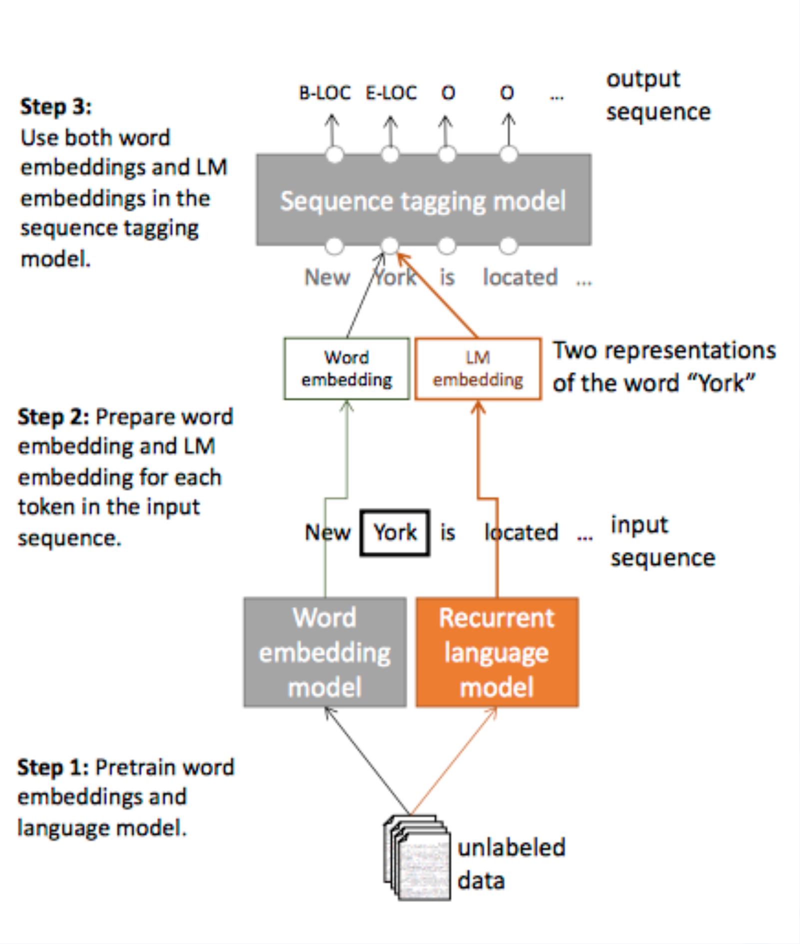
- It beats traditional models on Tagging, Chunking, Semantic Role Labelling and NER

System	accuracy
Combination of HMM, Maxent etc. (Florian et al., 2003)	88.76
MaxEnt classifier (Chieu., 2003)	88.31
Semi-supervised model combination (Ando and Zhang., 2005)	89.31
Conv-CRF (Collobert et al., 2011)	81.47
Conv-CRF (Senna + Gazetteer) (Collobert et al., 2011)	89.59
CRF with Lexicon Infused Embeddings (Passos et al., 2014)	**90.90**
BI-LSTM-CRF	84.26
BI-LSTM-CRF (Senna + Gazetteer)	90.10

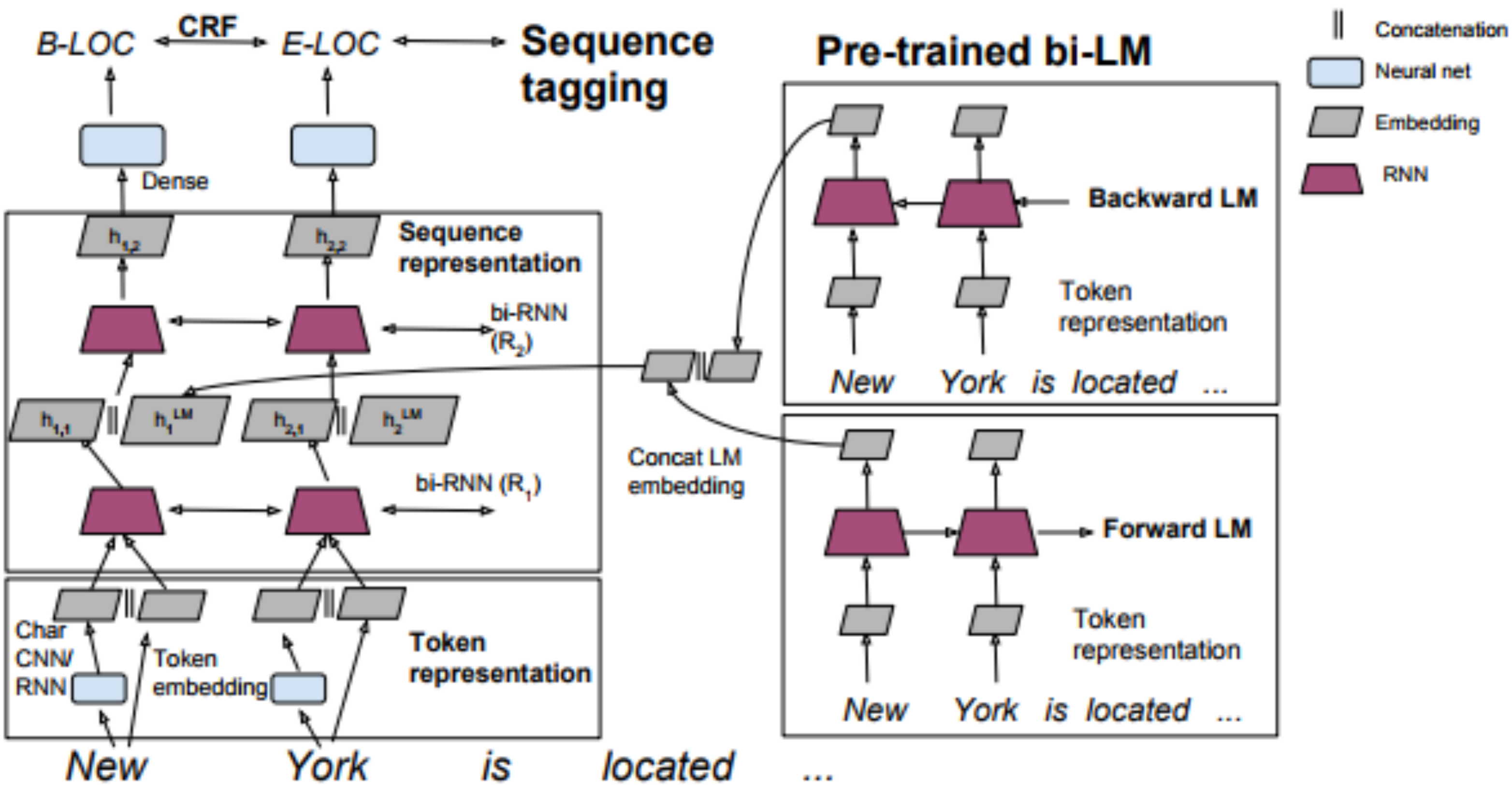
BiLSTM CRF


CRF Layer
BiLSTM Layer
$\overrightarrow{h}_{t-1}$
$\overrightarrow{h}_t$
$\overrightarrow{h}_{t+1}$
$\overleftarrow{h}_{t-1}$
$\overleftarrow{h}_t$
$\overleftarrow{h}_{t+1}$
$\overrightarrow{W}_i$
$\overleftarrow{W}_i$
$\overrightarrow{U}_i$
$\overleftarrow{U}_i$
Dropout
Dropout
Dropout
Input Layer

BiLSTM CRF with a touch of LM



BiLSTM CRF with a touch of LM



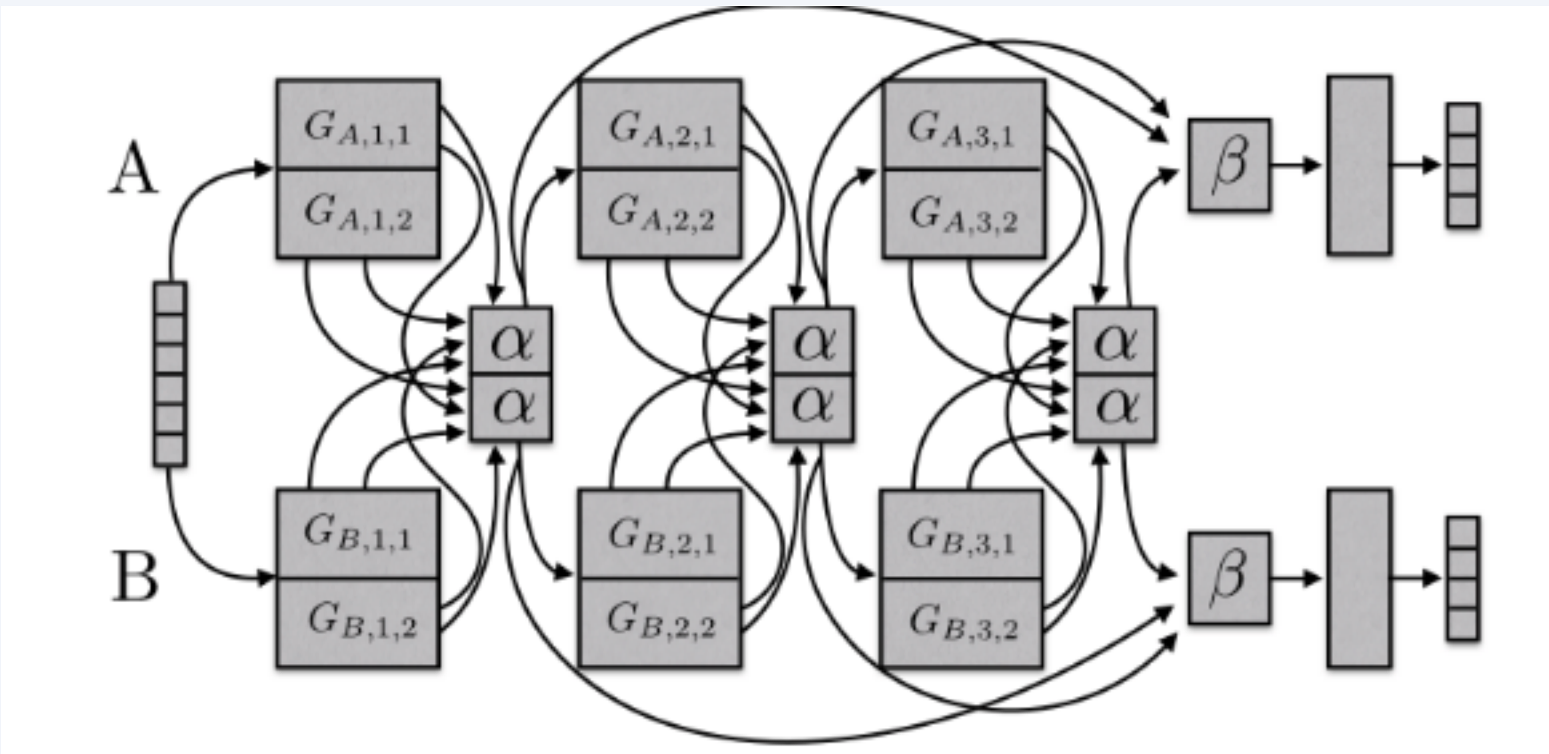
BiLSTM CRF with a touch of LM

Model	External resources	F_1 Without	F_1 With	Δ
Yang et al. (2017)	transfer from CoNLL 2000/PTB-POS	91.2	91.26	+0.06
Chiu and Nichols (2016)	with gazetteers	90.91	91.62	+0.71
Collobert et al. (2011)	with gazetteers	88.67	89.59	+0.92
Luo et al. (2015)	joint with entity linking	89.9	91.2	**+1.3**
	no LM vs TagLM *unlabeled data only*	90.87	**91.93**	+1.06

Multitasking

	Unlabelled			Labelled		
Method	**Precision**	**Recall**	**F1**	**Precision**	**Recall**	**F1**
Finkel et al. (2005)	77.89	50.27	61.10	49.90	27.97	35.85
Lample et al. (2016)	71.92	49.37	58.55	41.36	28.47	33.72
BiLSTM	81.58	57.86	67.71	45.80	32.48	38.01
BiLSTM + Chunking	82.88	52.08	63.96	55.54	34.90	42.86
BiLSTM + Framenet	77.86	56.05	65.18	54.04	38.91	45.24
BiLSTM + Hyperlinks	76.59	60.53	67.62	46.99	44.09	41.13
BiLSTM + Multi-word	74.80	70.18	**72.42**	46.99	44.09	**45.49**
BiLSTM + Super-sense	83.70	51.76	63.93	56.94	35.25	43.54

And yet another Multitasking: Sluice Network



And yet another Multitasking: Sluice Network

Named entity recognition								
System	nw (ID)	bc	bn	mz	pt	tc	wb	OOD Avg
Single task	95.04	93.42	93.81	93.25	94.29	94.27	92.52	93.59
Hard parameter sharing	94.16	91.36	93.18	93.37	**95.17**	93.23	**92.99**	93.22
Low supervision	94.94	91.97	93.69	92.83	94.26	93.51	92.51	93.13
Cross-stitch network	95.09	92.39	93.79	93.05	94.14	93.60	92.59	93.26
Sluice network	**95.52**	**93.50**	**94.16**	**93.49**	93.61	**94.33**	92.48	**93.60**

Challenges

- Long Documents vs Short Excerpts

  - Overgeneration
  - Infrequency
  - Redundancy
  - Evaluation

Thank You

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