Traitement Automatique des Langues Naturelles

Cours 8: Pragmatique et discours, analyse au-delà de la phrase

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Les niveaux d'analyse

- phonologie: les sons
- morphologie: les mots et leur forme
- syntaxe: l'organisation des mots en phrase
- sémantique: le sens dans la phrase
- **pragmatique: le sens en contexte**

What is discourse?

Introduction

- Texts and conversations are not just a random sequence of clauses and sentences.

I am in Torino to give an introductory course on Discourse Processing.

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I am in Torino to give an introductory course on Discourse Processing.

Viviana invited Farah to Torino. She enjoyed the city. They had diner together and ate delicious pasta.

Discourse analysis: Crossing sentence boundaries

Linguistic **phenomena between sentences**:

- Topics (topic segmentation),
- Temporal links,
- Entities and reference,
- Rhetorical/discourse relations

Discourse structure is about:

- revealing text coherence,
- interpreting documents (i.e. making inferences on its content),

There are links between the different types of **text organization**, e.g.:

- constraints discourse/temporal e.g. often the effect after the cause
- discourse/topic e.g. some relations require to keep the same topic
- discourse/coreference e.g. some relations block a potential referent

Cohesion

– Document: not a random sequence of sentences
– Cohesion (Halliday and Hasan, 1976): a text is cohesive if its elements are linked together

- Linking across entities through grammatical and lexical connections, including:
  - anaphoric expressions (e.g. '.. Farah ... She ...')
  - lexical relations (synonymy, meronymy, hyponymy) appearing across sentences
  - discourse connectives: trigger relations between sentences (e.g. and, after, because, meanwhile, as a result, on the contrary...)
- Cohesive elements are found in the discourse itself (lexicalized)

Cohesion

- A cohesive discourse

Viviana invited Farah to Torino. She enjoyed the city. They had diner together and ate delicious pasta.

Cohesion

- A cohesive discourse

Viviana invited Farah to Torino. She enjoyed the city. They had diner together and ate delicious pasta.

Cohesion

- A cohesive discourse

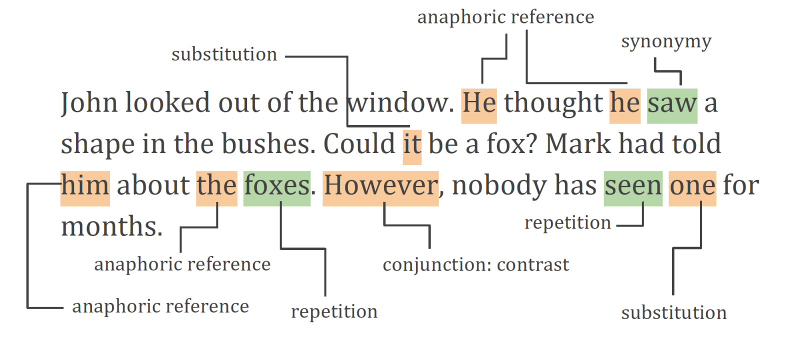
Viviana invited Farah to Torino. She enjoyed the city. They had diner together and ate delicious pasta.

- A non cohesive discourse: no lexicalized elements linking the sentences (but coherent)

Viviana invited Farah to Torino. Cristina prepared diner.

Cohesion

The big picture[1]



[1] Taken from Communicative effectiveness. Cohesion and coherence (I)

Coherence

A text is coherent if it makes sense

- Refers to **the logical structure of discourse** where every part of a text has a function, a role to play, with respect to other parts in the text (Taboada and Mann, 06).

Examples:

1. Paul fell. Marie helped him get up. (Narration)
2. Paul fell. Marie pushed him. (Cause)
3. Paul fell. He likes spinach. (??)
4. Paul went to Istanbul. He has to attend a conference. (Reason)
5. Paul went to Istanbul. He likes spinach. (? Reason)

Coherence

Cohesive but not coherent: i.e.: Each sentence is notionally linked to the one that precedes it, using both lexical and grammatical means, but the text is ultimately senseless

(1) *I am a teacher. The teacher was late for class. Class rhymes with grass. The grass is always greener on the other side of the fence. But it wasn't.* (Teacher resource site)

Automatic summarization: not cohesive not coherent i.e.: improper sentence ordering, pronoun without antecedent

(2) *It's like going to disney world for car buyers. I have to say that Carmax rocks. We bought it at Carmax, and I continue to have nothing bad to say about that company. After our last big car milestone, we've had an odyssey with cars.* [Mithun and Kosseim, 2011]

Coherence and coheson

Same phenomena in dialogues:

Example 1

165	lj	anyone want sheep for clay?
166	gwfs	got none, sorry :(
167	gwfs	**so how do people know about the league?**
168	wm	no
p 170	lj	**i did the trials**
174	tk	**i know about it from my gf**
175	gwfs	[**yeah me too,**]$_a$ [*are you an Informatics student then, lj?*]$_b$
176	tk	**did not do the trials**
177	wm	has anyone got wood for me?
178	gwfs	[**I did them**]$_a$ [**because a friend did**]$_b$
179	gwfs	lol wm, you cad
180	gwfs	afraid not :(
181	lj	[*no, I'm about to start math.*]$_a$ [*I just hang around appleton a lot*]$_b$
182	tk	sry no
183	gwfs	my single wood is precious
184	wm	what's a cad?

From STAC [Asher et al 2016]

Coherence and cohesion

Same phenomena in dialogues:

Conversation Sample	*Facilitative Strategies*
A: Where did you go today?	
R: We haven't left the place.	
A: You haven't left the place today?	Repetition
R: I don't think so.	
A: You didn't go to the Capitol today?	Cue
That big, old building, that big old white building	Cue, Cue
You didn't go there?	Repetition
R: I don't think so.	
A: You don't think so?	Repetition
Did you get on a bus today?	Cue
R: Huh?	
A: Did you get on a bus today?	Repetition
R: Yes.	
A: You got on a bus?	Repetition
R: And that's where we went.	
A: Yes, to the Capitol.	Cue
R: Umm hmm.	
This is my problem. My recaller is on vacation. (..)	
Maybe you can help me find it.	

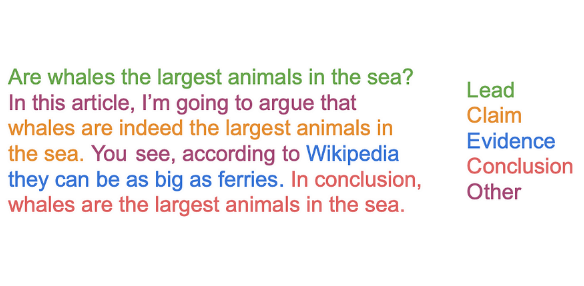
My Recaller is on Vacation: Discourse Analysis of Nursing-Home Residents With Dementia [Dijkstra et al. 2002] [9]

Document-level structures

Textual organization

Different types of organization:

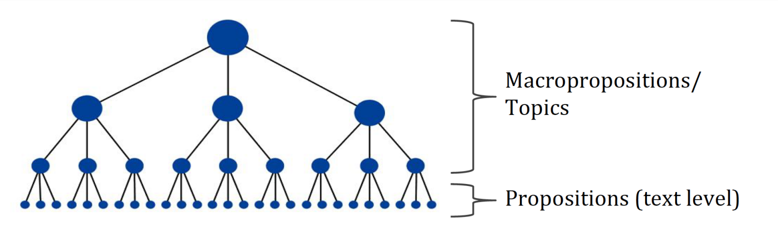
- topical structure: identify topic chains, change in topics ...
- coreference: identify the referents of entities, chains of coreference
- discourse structure: identify the (semantic) links between sentences / clauses (contrast, explanation ...)
- argumentative structure: identify the argumentation strategies, specific elements = claim / arguments / evidence (argument mining)



https://towardsai.net/p/machine-learning/argminer-end-to-end-argument-mining

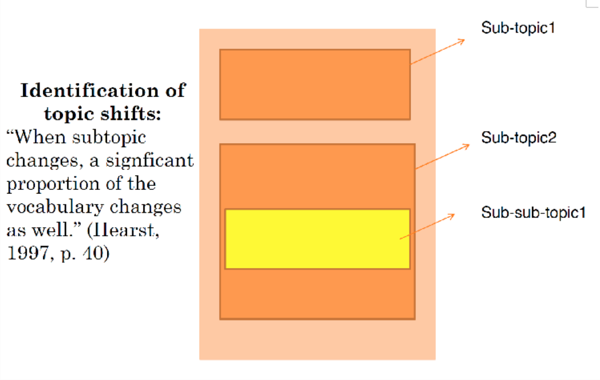
Topic-based structure

- Focus on "multi-level" text spans and signals of global text organization
- Split discourse into a linear sequence of segments
- Each segment focuses on a distinct subtopic occurring in the context of one or more main topics.



Topic-based structure

Guided by lexical usage (word repetition, discourse connectives, and paradigmatic relations).



Topic modeling

Mainly unsupervised approach to uncover topics: annoation is hard, with issues when transfering to new domains.

$\rightarrow$ Topic models are statistical tools for discovering the hidden semantic structure in a collection of documents (Blei et al., 2003; Blei, 2012)

- TextTiling for topic segmentation (Hearst, 1997): compute the textual similarity between each pair of adjacent blocks of text (sentences or fixed-length units), using a formula such as the smoothed cosine similarity of their bag-of-words vectors
- Most topic models build on latent Dirichlet allocation (LDA) (Blei et al., 2003). = a hierarchical probabilistic model that represents each topic as a distribution over terms and represents each document as a mixture of the topics ; each observed word is assigned to a particular topic.

Source: Topic Modeling in Embedding Spaces, 2020 ; survey, 2017

Topic modeling

Topic Modeling in Embedding Spaces, 2020: Each term is represented by an embedding and each topic is a point in that embedding space.

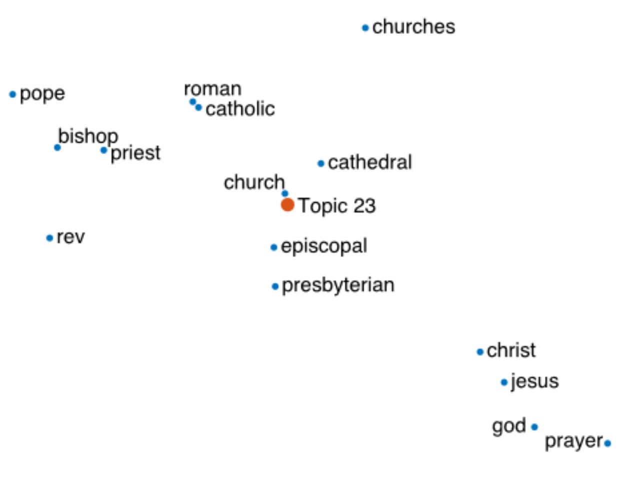
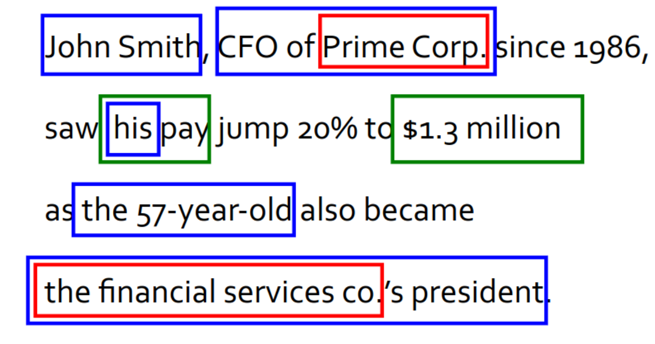


Figure 2: A topic about Christianity found by the ETM

Coreference

Another document-level organization: coreference

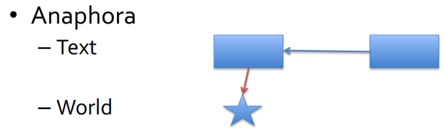
- Identify all noun phrases (mentions) that refer to the same real world entity
- Noun phrases refer to entities in the world, many pairs of noun phrases co-refer, some nested inside others

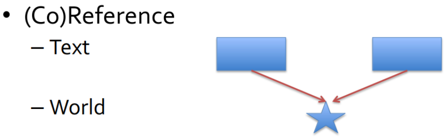


Borrows slides from Manning

Coreference vs Anaphora

- **Coreference** is when two mentions refer to the same entity in the world
- **anaphora** is when a term (anaphor) refers to another term (antecedent) and the interpretation of the anaphor is in some way determined by the interpretation of the antecedent





$\rightarrow$ Not all anaphoric relations are coreferential: bridging anaphora

ex. *We went to see* ***a concert*** *last night.* ***The tickets*** *were really expensive*

Coreference resolution

Tasks: groups entity mentions into sets of mentions that refer to the same real-world entities

- Mention detection: dentifying the mentions (nouns, pronouns etc)
- Mention linking: identifying the links between mentions / clustering the detected mentions

$\rightarrow$ cast as word-level binary classification problems (eval = F1) or more complicated if mentions belong to multiple coreference clusters and each cluster could contain multiple mentions (eval = e.g. MUC)

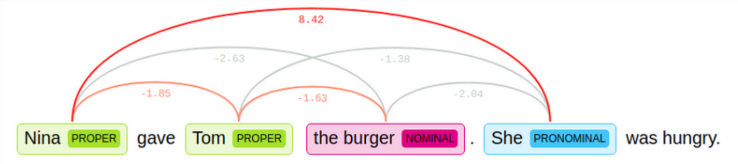
$\rightarrow$ Some joint approaches (Lee et al. 2018; Joshi et al. 2020) but still often distinct tasks (Khosla and Rose 2020; Caciularu et al. 2021).

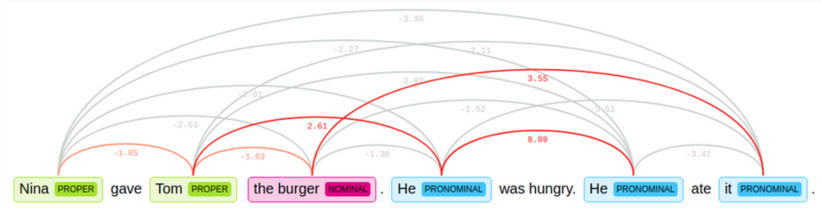
Coreference Resolution through a seq2seq Transition-Based System, 2022: predict mentions and links jointly, 83.3 F1-score for English ; 68.5 F1-score for Arabic and 74.3 F1-score for Chinese.

Main source: survey paper

Coreference resolution

Examples from Neuralcoref (by HuggingFace), try it:
`https://huggingface.co/coref/`





Coreference resolution: applications

- Full text understanding – understanding an extended discourse
- Machine translation (if languages have different features of gender, number, etc.)
- Text summarization
- Tasks like information extraction and question answering, when some sentences have pronouns

Discourse / Rhetorical structure

- **semantic or pragmatic relations** among units to produce the overall meaning of a discourse (Hobbs,79; Grosz et al., 95)
- discourse / coherence / rhetorical relations: can be **explict** = trigered by a discourse connective (e.g. but, otherwise, if..then ... `http://connective-lex.info/`) or **implicit**
- **different frameworks** with different **constraints** (e.g. RST [Mann and Thompson, 88], SDRT [Asher, 1993]) and different **relation sets** (e.g. Elaboration, Explanation, Cause, Concession, Consequence, Condition)

1. The tawny owl is a nocturnal bird of prey, **but** it can live in the daytime.
2. The towers collapsed less than two hours later (Result) *dragging* down with them the building of the Marriott World Trade Center. (Sequence) The tower 7 of the WTC collapsed in the afternoon *because of* damages caused by the fall of Twin Towers.

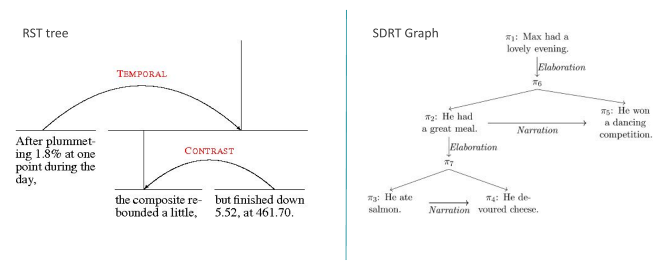
From Annodis

Discourse parsing

⟶ Discourse analysis / parsing relies on 3 sub-tasks:

- **Discourse segmentation**: What are the discourse units?
- **Unit attachment**: How do these units attach to other units?
- **Labelling**: How discourse units are linked? i.e. What are the relations that bind distinct discourse units into a coherent whole?

Hierarchical structure of discourse:



Discourse parsing

$\longrightarrow$ Tree / graph building: using the same algorithms as for syntax, with specific challenges:

- Input representation = long segments
- Labelling:
    - semantic links relying on information at many levels, i.e. morpho-syntax, semantics, world knowledge
    - interaction between pairs of segments and the rest of the document
    - large label set (around 20-30 labels, up to 100) and skewed distribution
- Data scarcity: annotation is hard, datasets are small

1. Paul est tombé. Marie l'a poussé.
2. Paul est tombé. Marie l'a poussé pour éviter qu'il ne se fasse écraser.
3. Kim switched off the light. The room became dark. Kim drew the blinds.
4. Kim switched off the lights (and) Kim drew the blinds. The room became dark.

Ex. 3 and 4 from [Asher and Lascarides 2003; Bender and lascarides 2019]

Discourse corpora

DISRPT 23

Corpus	Domain	#Docs	#Sents	#Tokens	Vocab	#EDUs	#Conn	#Labels	#Rels	References
Tasks 1 and 3: EDU Segmentation and Relation Classification										
deu.rst.pcc	newspaper commentaries	176	2,193	33,222	8,359	3,018	-	26	2,665	Potsdam Commentary Corpus (Stede and Neumann, 2014)
**eng.dep.covdtb	scholarly paper abstracts on COVID-19 and related coronaviruses	300	2,343	60,849	8,293	5,705	-	12	4,985	COVID-19 Discourse Dependency Treebank (COVID19-DTB) (Nishida and Matsumoto, 2022)
eng.dep.scidtb	scientific articles	798	4,202	102,493	8,700	10,986	-	24	9,904	Discourse Dependency Tree-Bank for Scientific Abstracts (SciDTB) (Yang and Li, 2018)
**eng.rst.gentle	multi-genre	26	1,334	17,797	4,135	2,708	-	31	2,540	Genre Tests for Linguistic Evaluation (GENTLE) (Aoyama et al., 2023)
eng.rst.gum	multi-genre	213	11,656	203,879	19,404	26,252	-	14	24,688	Georgetown University Multi-layer corpus V9 (Zeldes, 2017)
eng.rst.rstdt	news	385	8,318	205,829	19,160	21,789	-	17	19,778	RST Discourse Treebank (Carlson et al., 2001)
eng.sdrt.stac	dialogues	45	11,087	52,354	3,967	12,588	-	16	12,235	Strategic Conversations corpus (Asher et al., 2016)
eus.rst.ert	medical, terminological and scientific	164	2,380	45,780	13,662	4,202	-	29	3,825	Basque RST Treebank (Iruskieta et al., 2013)
fas.rst.prstc	journalistic texts	150	2,179	66,694	7,880	5,853	-	17	5,191	Persian RST Corpus (Shahmohammadi et al., 2021)
fra.sdrt.annodis	news, wiki	86	1,507	32,699	7,513	3,429	-	18	3,338	ANNOtation DIScursive (Afantenos et al., 2012).
nld.rst.nldt	expository texts and persuasive genres	80	1,651	24,898	4,935	2,343	-	32	2,264	Dutch Discourse Treebank (Redeker et al., 2012)
por.rst.cstn	news	140	2,221	58,793	7,786	5,537	-	32	4,993	Cross-document Structure Theory News Corpus (Cardoso et al., 2011)
rus.rst.rrt	blog and news	332	23,044	473,005	75,285	41,532	-	22	34,566	Russian RST Treebank (Toldova et al., 2017)
spa.rst.rststb	multi-genre	267	2,089	58,717	9,444	3,351	-	28	3,049	RST Spanish Treebank (da Cunha et al., 2011)
spa.rst.sctb	multi-genre	50	516	16,515	3,735	744	-	25	692	RST Spanish-Chinese Treebank (Spanish) (Cao et al., 2018)
zho.dep.scidtb	scientific	109	609	18,761	2,427	1,407	-	23	1,298	Discourse Dependency Tree-Bank for Scientific Abstracts (SciDTB) (Yi et al., 2021; Cheng and Li, 2019)
zho.rst.gcdt	multi-genre	50	2,692	62,905	9,818	9,706	-	31	8,413	Georgetown Chinese Discourse Treebank (GCDT) (Peng et al., 2022b,a)
zho.rst.sctb	multi-genre	50	580	15,496	2,973	744	-	26	692	RST Spanish-Chinese Treebank (Chinese) (Cao et al., 2018)

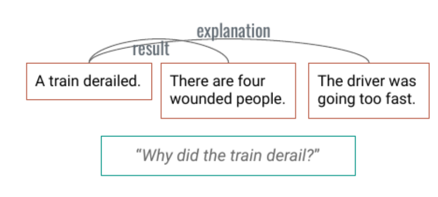
Discourse parsing (on English)

- bottom-up with representation learning [Ji and Eisenstein, 2016], 2-stage system [Wang et al 2017], multi-task [Braud et al, 2016] ..
- Top-down parsing using Pointer Networks [Lin et al 2019; Liu et al 2019] (sentence-level), with a splitting mechanism [Kobayashi et al 2020; Zhang et al 2020; **Koto et al 2021**]
- Recent work: distant supervision based on sentiment analysis or summarization [Huber and Carenini 2020, Xiao et al 2021]

Method	S	N	R	F
Bottom Up:				
Feng and Hirst (2014)*†	68.6	55.9	45.8	44.6
Ji and Eisenstein (2014)*†	64.1	54.2	46.8	46.3
Surdeanu et al. (2015)*†	65.3	54.2	45.1	44.2
Joty et al. (2015)*	65.1	55.5	45.1	44.3
Hayashi et al. (2016)*	65.1	54.6	44.7	44.1
Li et al. (2016)*	64.5	54.0	38.1	36.6
Braud et al. (2017)*	62.7	54.5	45.5	45.1
Yu et al. (2018) (static)‡	71.1	59.7	48.4	47.4
Yu et al. (2018) (dynamic)‡	71.4	60.3	49.2	48.1
Top Down:				
Zhang et al. (2020)*	67.2	55.5	45.3	44.3
Our model				
Transformer (static)‡	70.6	59.9	50.6	49.0
Transformer (dynamic)‡	70.2	60.1	50.6	49.2
LSTM (static)‡	72.7	61.7	50.5	49.4
LSTM (dynamic)‡	**73.1**	**62.3**	**51.5**	**50.3**
Our best model without paragraph boundary feature				
LSTM (static)	66.3	56.6	47.1	46.1
LSTM (dynamic)	67.3	57.4	48.5	47.4
Human	78.7	66.8	57.1	55.0

Discourse parsing: applications

- extract / build document structures
- representing their meaning → Correspond to a fine-grained representation of a document that could allow to make inference on its content
- e.g. Question Answering, Summarization, Translation...



Exemples d'utilisation : analyse d'articles

- Travail en groupe $\longrightarrow$ Chaque groupe choisit un article
- Lecture de l'article puis restitution 5-10min par groupe
  - Quelle est la tâche abordée ?
  - Quelles sont les données utilisées ? Notamment quel type d'entrée, étiquette à quel niveau ?
  - Quelle est la méthodologie générale, comment est intégrée l'information discursive ?
  - Quelle est l'architecture utilisée pour cette tâche ?
  - Quelles sont les métriques d'évaluation ?
  - Quelles sont les performances de ces modèles comparées aux baselines?
  - Quel est votre avis personnel ?

Exemples d'utilisation : analyse d'articles

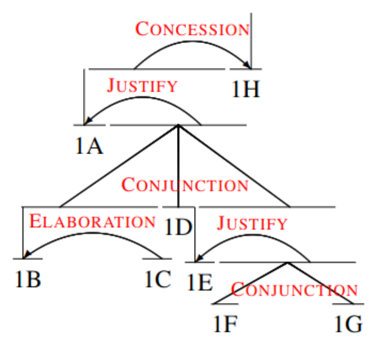
- Better Document-level Sentiment Analysis from RST Discourse Parsing, 2016
- Discourse-Aware Neural Extractive Text Summarization, 2020
- Multi-Task Learning for Depression Detection in Dialogs, 2022
- An Integrated Approach for Political Bias Prediction and Explanation Based on Discursive Structure, 2022
- Document Structure in Long Document Transformers, 2024

Additional readings:

- **A Pragmatics-Centered Evaluation Framework for Natural Language Understanding**
- **BLONDE: An Automatic Evaluation Metric for Document-level Machine Translation**
- **When and Why is Document-level Context Useful in Neural Machine Translation?**
- **A Survey on Document-level Neural Machine Translation: Methods and Evaluation**
- **Dynamic Context Selection for Document-level Neural Machine Translation via Reinforcement Learning, 2020**
- **KALM: Knowledge-Aware Integration of Local, Document, and Global Contexts for Long Document Understanding**
- **When Does Translation Require Context? A Data-driven, Multilingual Exploration**

Better Document-level Sentiment Analysis from RST Discourse Parsing, 2016

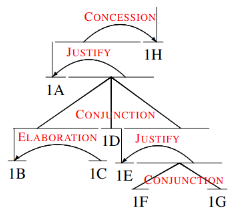
[It could have been a great movie]^{1A} [It does
beautiful scenery,]^{1B} [some of the best since L
the Rings.]^{1C} [The acting is well done,]^{1D} [and I
liked the son of the leader of the Samurai.]^{1E} [H
a likable chap,]^{1F} [and I hated to see him die.]^{1G}
other than all that, this movie is nothing more tha
den rip-offs.]^{1H}



Discourse and sentiment analysis

Better Document-level Sentiment Analysis from RST Discourse Parsing, 2016

- 1. Repondération de la contribution de chaque unité de discours basée sur sa position, combiné à un analyseur de sentiment basé sur un lexique ou un classifieur
- 2. Propagation récursive du sentiment de bas en haut de l'arbre discours RST (RecNN)



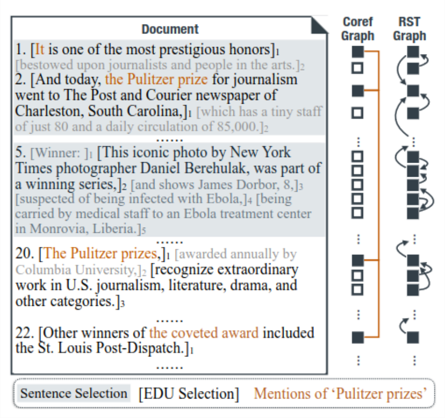
	Pang & Lee	Socher et al.
Baselines		
B1. Lexicon	68.3	74.9
B2. Classifier	82.4	81.5
Discourse depth weighting		
D1. Lexicon	72.6	78.9
D2. Classifier	82.9	82.0
Rhetorical recursive neural network		
R1. No relations	83.4	85.5
R2. With relations	84.1	85.6

Table 1: Sentiment classification accuracies on two movie review datasets (Pang and Lee, 2004; Socher et al., 2013), described in Section 2.3.

Discourse and summarization (DiscoBERT)

Discourse-Aware Neural Extractive Text Summarization, 2020

Figure 1: Illustration of DISCOBERT for text summarization. Sentence-based BERT model (baseline) selects whole sentences 1, 2 and 5. The proposed discourse-aware model DISCOBERT selects EDUs 1- 1, 2-1, 5-2, 20-1, 20-3, 22-1. The right side of the figure illustrates the two discourse graphs we use: (i) Coref(erence) Graph (with the mentions of 'Pulitzer prizes' highlighted as examples); and (ii) RST Graph (induced by RST discourse trees).



Discourse and summarization (DiscoBERT)

Discourse-Aware Neural Extractive Text Summarization, 2020

- Segmentation en EDUs plutôt que phrases : plus fin, moins redondant
- Graphes RST : dépendances à longue portée entre EDUs [Ji and Eisenstein, 2014]
- Graphes de coréférence : modélisation d'un contexte large
- Encoder de document basé sur BERT, Graph Convolutional Networks pour encoder les graphes

Model	R-1	R-2	R-L
Lead3	40.42	17.62	36.67
Oracle (Sentence)	55.61	32.84	51.88
Oracle (Discourse)	61.61	37.82	59.27
NeuSum (Zhou et al., 2018)	41.59	19.01	37.98
BanditSum (Dong et al., 2018)	41.50	18.70	37.60
JECS (Xu and Durrett, 2019)	41.70	18.50	37.90
PNBERT (Zhong et al., 2019)	42.39	19.51	38.69
PNBERT w. RL	42.69	19.60	38.85
BERT (Zhang et al., 2019)	41.82	19.48	38.30
HIBERT$_S$	42.10	19.70	38.53
HIBERT$^*_S$	42.31	19.87	38.78
HIBERT$^*_M$	42.37	19.95	38.83
BERTSUM (Liu and Lapata, 2019)	**43.25**	20.24	**39.63**
T5-Base (Raffel et al., 2019)	42.05	**20.34**	39.40
BERT	43.07	19.94	39.44
DiscoBERT	43.38	20.44	40.21
DiscoBERT w. $\mathcal{G}_C$	43.58	20.64	40.42
DiscoBERT w. $\mathcal{G}_R$	43.68	20.71	40.54
DiscoBERT w. $\mathcal{G}_R$ & $\mathcal{G}_C$	**43.77**	**20.85**	**40.67**

Table 2: Results on the test set of the CNNDM dataset. ROUGE-1, -2 and -L F_1 are reported. Models with the asterisk symbol (*) used extra data for pre-training. R-1 and R-2 are shorthands for unigram and bigram overlap; R-L is the longest common subsequence.

Shallow discourse and depression

Multi-Task Learning for Depression Detection in Dialogs, 2022: DAIC-WOZ

- multi-modal semi-structured clinical interviews
- create a computer agent that interviews people and identifies verbal and nonverbal indicators of mental illness, PTSD and depression
- Different types of interviews: human or virtual interviewer

Face-to-face

Interviewer Let's see, is there someone in your life that's been a really positive influence for you?
Participant Uh yeah, my husband, yeah.
Interviewer Yeah.
Interviewer What kind of values did you take away from him?
Participant Uh he's always uh thinking ahead and looks at the big picture and doesn't uh mull over trivial things so that's something that helped me.
Interviewer Mhm yeah, those are good traits to have.
Participant Yeah, yes.
Interviewer Um how did you guys meet?

Wizard-of-Oz

Ellie Who's someone that's been a positive influence in your life?
Participant Uh my father.
Ellie Can you tell me about that?
Participant Yeah, he is a uh
Participant He's a very he's a man of few words
Participant And uh he's very calm
Participant Slow to anger
Participant And um very warm very loving man
Participant Responsible
Participant And uh he's a gentleman has a great sense of style and he's a great cook.
Ellie Uh huh
Ellie What are you most proud of in your life?

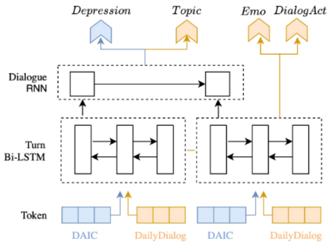
Autonomous

Ellie Who's someone that's been a positive influence in your life?
Participant My mom
Participant Has been a positive influence
Ellie Tell me more about that
Participant Well she's just always really nice and
Participant Considerate and upbeat and
Participant Sh just positive person
Ellie How would your best friend describe you?
Participant Outgoing funny
Participant A little bit
Participant Foolish <laughter>

Shallow discourse and depression

Multi-Task Learning for Depression Detection in Dialogs, 2022

→ Identification de personnes souffrant de dépression à partir de données annotées en émotion, en **topic** et en **actes de dialogue**.



	F_1	Prec.	Rec.	Acc.
BSL Majority vote	41.3	35.1	50.0	70.2
State-of-the-art				
NHN (baseline) [5]	45	-	50	-
HCAN [5]	63	-	66	-
HAN+L [6]	70	-	70	-
Ours				
STL Depression	43.9	44.5	47.5	63.8
MTL +Emo	55.5	56.2	61.6	70.2
MTL +Top	55.6	55.9	56.8	59.6
MTL +Diag	60.8	60.6	61.4	66.0
MTL +Emo+Diag+Top	**70.6***	**70.1**	**71.5***	**74.5**

Latent discourse and bias

An Integrated Approach for Political Bias Prediction and Explanation Based on Discursive Structure, 2023 → Etude de biais politiques mais sans analyseurs discursifs, via des structures latentes (+ découpage en EDUs vs phrases)

"The Virginia Beach shooter put a sound suppressor (...) so that the death shots were muffled, perhaps denying others the warning that would have allowed them to escape. It is long past time to remove the silencer that seems to suppress action on gun-control legislation, to treat mass shooting as the epidemic it is, and do everything possible to save lives.'" **(Washington Post, left-leaning)**

"The attack began shortly after 16:00 (20:00 GMT), at Virginia Beach Municipal Center, in an area which is home to a number of city government buildings. The area was put into lockdown by police and employees were evacuated. 'We just heard people yelling and screaming at people to get down,' Megan Banton, an administrative assistant in the building, told local television news station WAVY." **(BBC, center)**

"The chilling fact is that mass public killers are attracted to targets where people can't defend themselves. (...) Ninety-eight percent of US mass public shootings since 1950 have occurred in places where people weren't allowed to defend themselves. But the news media refuses to cover this fact, which illustrates the need for self-defense, not for more gun control that doesn't work." **(Townhall, right-leaning)**

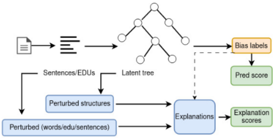


Figure 1: Overview of the approach: a supervised classification model relies on latent structures over textual units, and a module provides perturbation-based explanations, relying on various levels of analysis: words, sentences, EDUs, or latent trees.

Model	Allsides	C-POLITICS	HP
Literature			
Baly et al. (2020)	51.41*	-	-
Jiang et al. (2019)	-	-	82.2*
Fine-tuned PLMs			
RoBERTa	52.63	49.24	80.41
Longformer-4096	56.11	55.07	85.23
POLITICS	**60.44**	**60.52**	**85.82**
Structure-based models			
Structured Attention/Sent	48.76	48.57	75.63
Structured Attention/EDU	54.39	53.61	78.73

Table 2: Accuracy% (test set). ∗ indicates results not

Latent discourse and bias

An Integrated Approach for Political Bias Prediction and Explanation Based on Discursive Structure, 2023

→ Prédiction des biais + explication

Model	Allsides	C-POLITICS	HP
Literature			
Baly et al. (2020)	51.41*	-	-
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Table 2: Accuracy% (test set). ∗ indicates results not reproduced, taken from the original papers. Note that