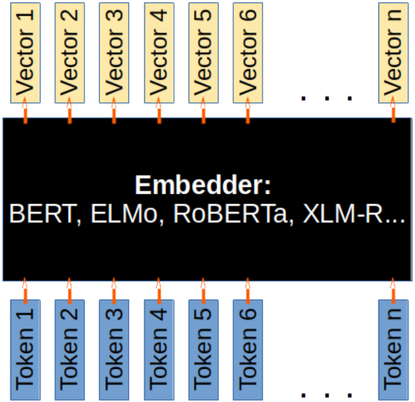
Computational approaches to semantic change detection
Day 3
Learned representations for semantic change detection part 2: contextualized embeddings and pre-trained language models

Andrey Kutuzov, Lidia Pivovarova

University of Oslo, University of Helsinki

Contextualized Embeddings



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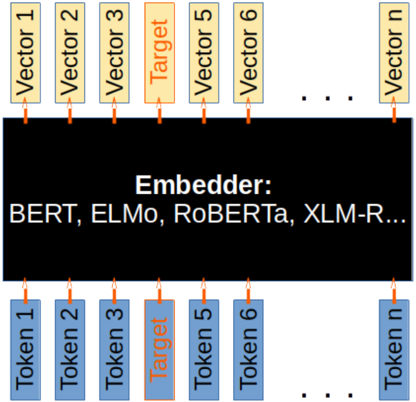

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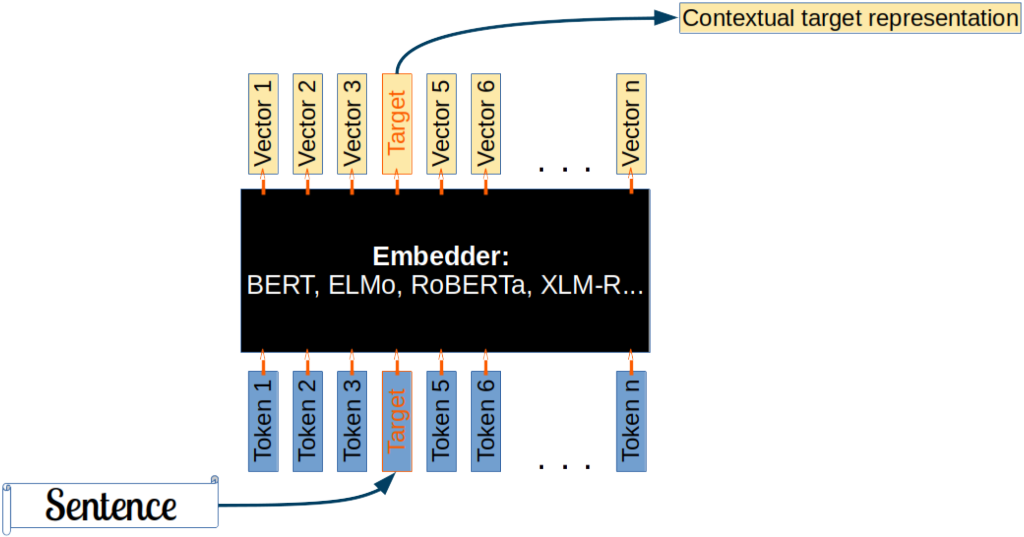

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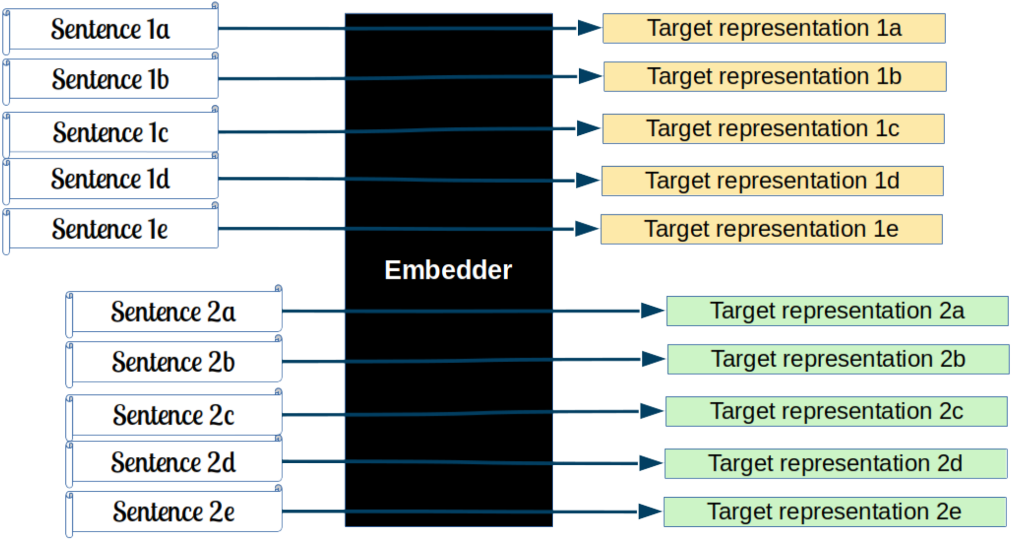

Contextualized Embeddings

- While static embeddings allows for **one word representation per corpus**
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- thus preserving much more information, accounting for polysemy and enabling interpretability.

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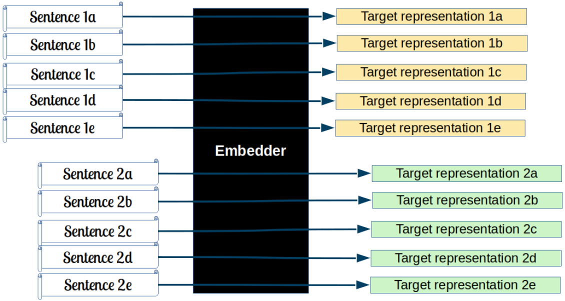
How to use these embeddings, specifically?



Form-based vs. sense-based methods

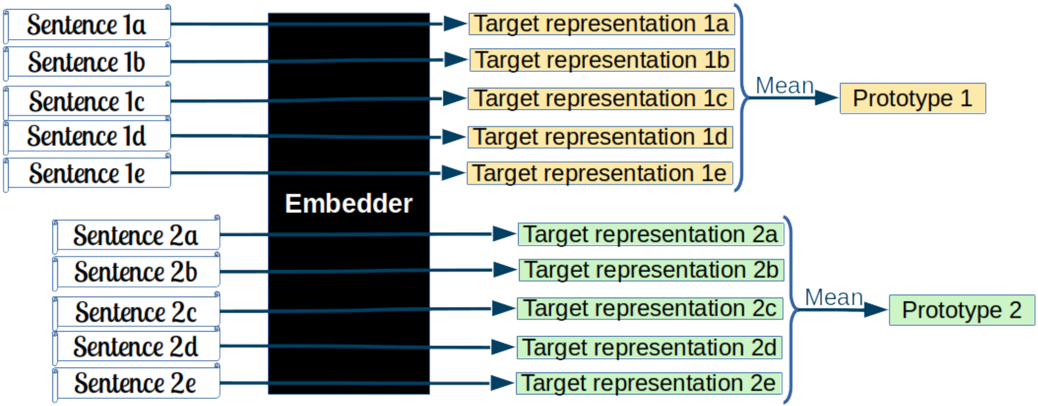
Methods using contextualized embeddings

Form-based: the meaning representation concerns the high-level properties of a target word, e.g. degree of polysemy or a dominant sense

Sense-based: the meaning representation concerns the low-level properties of a target word, i.e. different word usages (multiple meanings)

[Montanelli and Periti, 2023, Giulianelli et al., 2020]

Averaging



Degree of change: cosine distance between prototypes [Martinc et al., 2020a].

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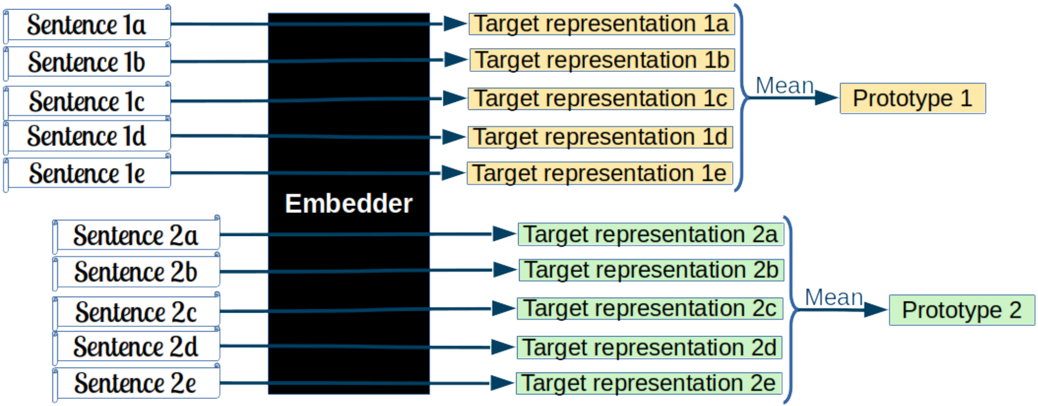
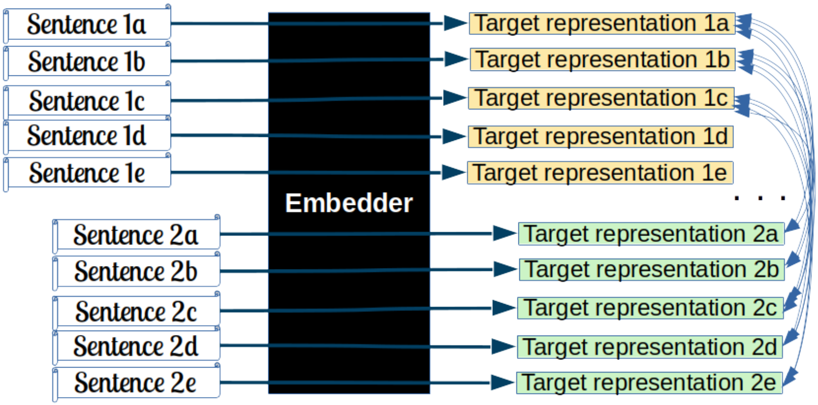


Degree of change: cosine distance between prototypes [Martinc et al., 2020a].

$$PRT = 1/cosine\_similarity(prototype1, prototype2)$$ [Kutuzov and Giulianelli, 2020]

Distances



Degree of change: averaged pairwise distance (APD) [Giulianelli et al., 2020].

Form-based methods

Form-based methods are straightforward to compute but not easily interpretable – an advantage of nuanced representation is lost as all word mentions in the corpus are collapsed into a single representation.

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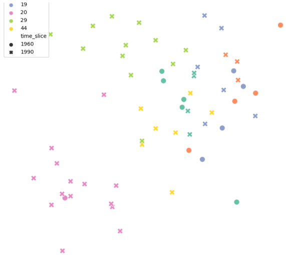
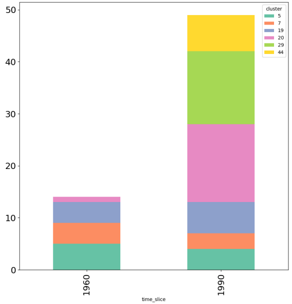
Stay tuned, we'll elaborate on interpretability problem on Friday

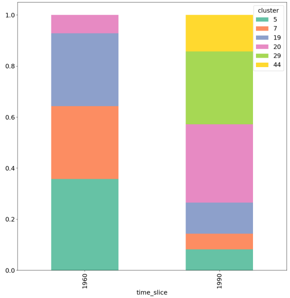
Clustering



1. Clustering

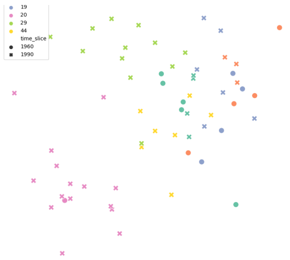


2. Cluster distributions



3. Divergence

Clustering



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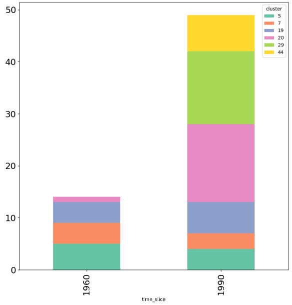

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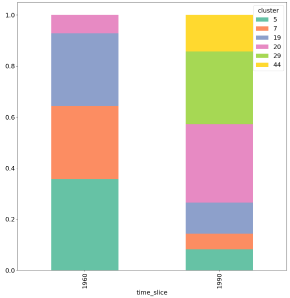


3. Divergence

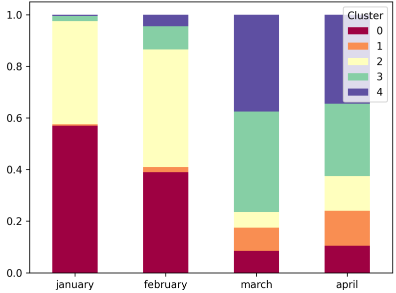
Jensen-Shannon divergence [Martinc et al., 2020b, Giulianelli et al., 2020]

$$JSD(P_w^1, P_w^2) = 1/2(KL(P_w^1||M) + KL(P_w^2||M))$$

$$M = (P_w^1 + P_w^2)/2$$

$$KL(P||M) = \sum_{x \in X} P(x) log(\frac{P(x)}{M(x)})$$

Clustering: interpretation



2020 news: cluster distributions per month for word *strain* and top-10 tf-idf keywords for each cluster [Montariol et al., 2021].

#	Keywords
0	strain coronavirus, new strain, city wuhan, novel strain, strain virus, chinese city
1	strain health, strain resources, stream, network infrastructure, international resources, likely strain
2	new strain, acute respiratory, 2019 ncov, respiratory syndrome, severe acute, identified humans
3	financial strain, feeling strain, strain coronavirus, economic strain, signs strain, strain said
4	ease strain, putting strain, strain health, reduce strain, care system, strain hospitals

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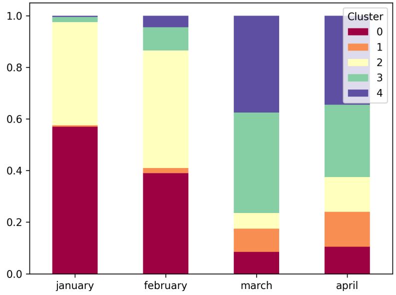

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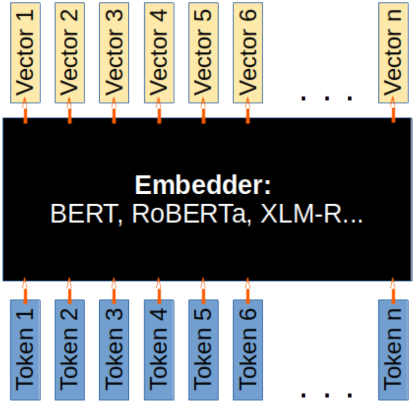
But: correspondence between clusters and *senses* is unclear; number of clusters, clustering method affect results; top-performing method is not necessary the most interpretable.

Substitutes



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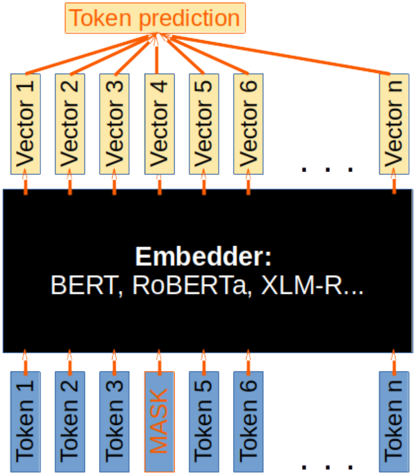

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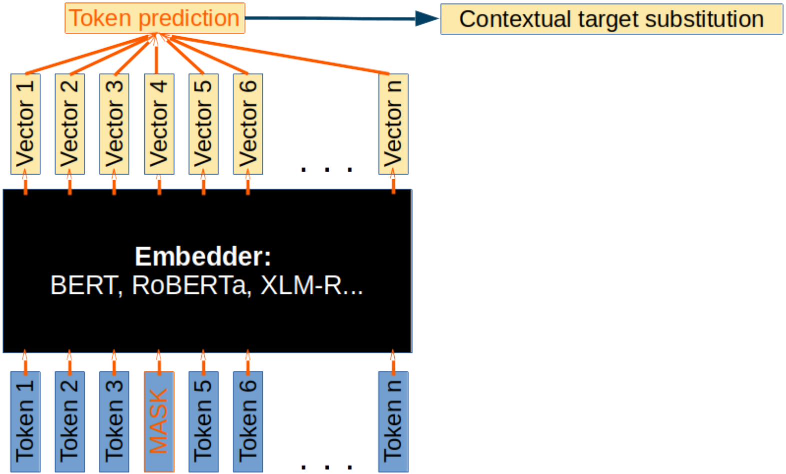

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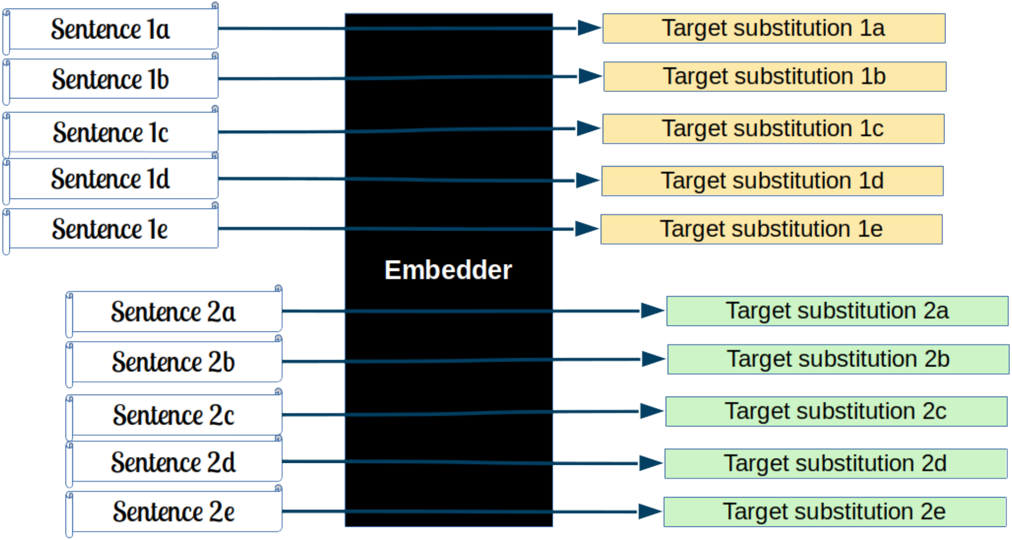

Substitutes

Word	SE rating	SE rank	Scaled JSD	Scaled JSD rank	Corpus A substitutes (1810–1860)	Corpus B substitutes (1960–2010)
plane	0.88	1	0.97	1	plane line planes point surface lines	plane aircraft planes jet airplane car
graft	0.55	4	0.97	2	tree plant stock vine fruit wood	corruption bribery fraud crime violence
tip	0.68	2	0.85	7	tipped tip covered end filled tips give	tip tips end tipped edge point top ends
gas	0.16	23	0.72	14	gas gases vapor air fire water	gas gasoline oil gases fuel water air
head	0.30	10	0.68	16	head face hand heads hands eyes	head face heads hand body hands eyes
bit	0.31	9	0.51	23	bit piece sort little pieces bits kind	bit little lot touch tad piece bits pieces
fiction	0.02	35	0.41	27	fiction history literature art poetry	fiction fact fantasy story stories novels
tree	0.07	33	0.22	33	trees tree plants branches plant wood	trees tree plants woods branches bushes
ounce	0.28	11	0.08	37	ounce inch pounds hour acre dollars	ounce pounds inch inches cups pieces

Table 2: Example terms from the SE English dataset, showing the most common substitutes from our approach.

[Card, 2023]

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Same issues: correspondence between substitutions and *senses*, hyperparameters...

1. Contextualized Embeddings
2. Form-based methods
3. Sense-based methods
4. **Supervised methods**
5. Time-awareness
6. Performance

Supervised methods

- Most methods for semantic shift detection are unsupervised
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- Most methods for semantic shift detection are unsupervised
  - the main reason is the lack of training data due to difficulty in manual annotation for this task
- When training data exists LLMs show their potential

Direct supervision

RuShiftEval—the only shared task (so far) that included a training set: the same language (Russian) and the same time periods (before/after 1917 and before/after 1991) [Kutuzov and Pivovarova, 2021]. Three best-performing solutions used the training set to explicitly emulate the annotation process.

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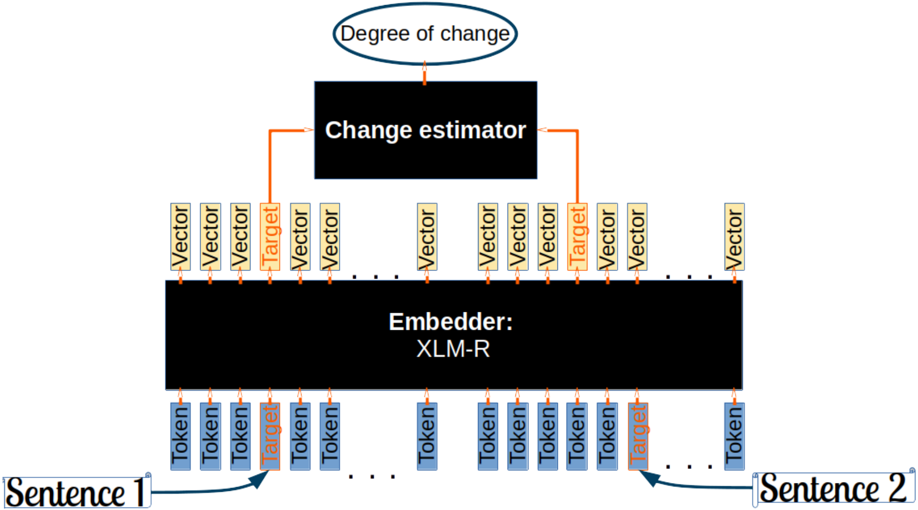
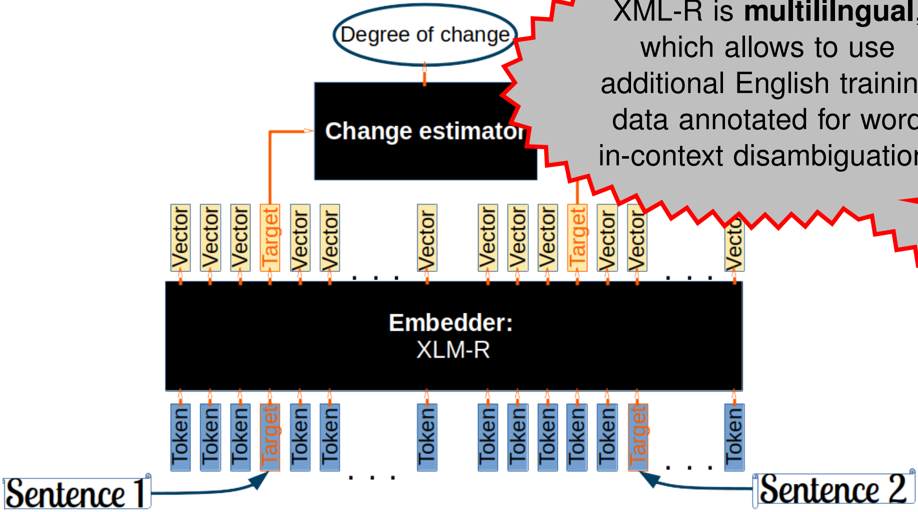
	Team	RuShiftEval1	RuShiftEval2	RuShiftEval3	Mean	Type
1	**GlossReader**	0.781	**0.803**	**0.822**	**0.802**	token
2	**DeepMistake**	**0.798**	0.773	0.803	0.791	token
3	vanyatko	0.678	0.746	0.737	0.720	token
4	aryzhova	0.469	0.450	0.453	0.457	token
5	Discovery	0.455	0.410	0.494	0.453	token
6	UWB	0.362	0.354	0.533	0.417	type
7	dschlechtweg	0.419	0.373	0.383	0.392	type
8	jenskaiser	0.430	0.310	0.406	0.382	token
9	SBX-HY	0.388	0.281	0.439	0.369	type
	Baseline	0.314	0.302	0.381	0.332	type

Direct supervision



[Arefyev et al., 2021]

Direct supervision



XML-R is **multililngual**, which allows to use additional English training data annotated for word in-context disambiguation.

[Arefyev et al., 2021]

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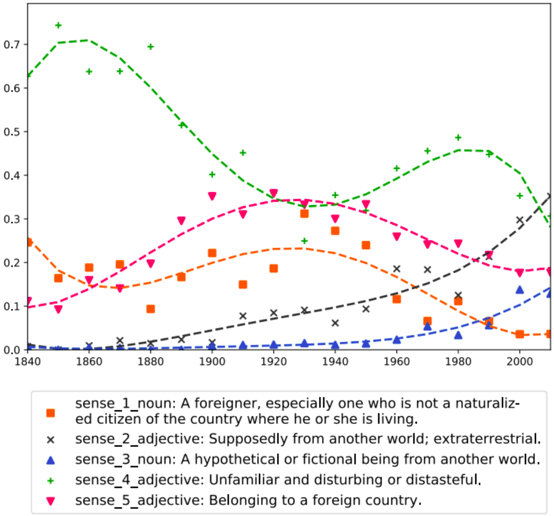

(b) *alien*

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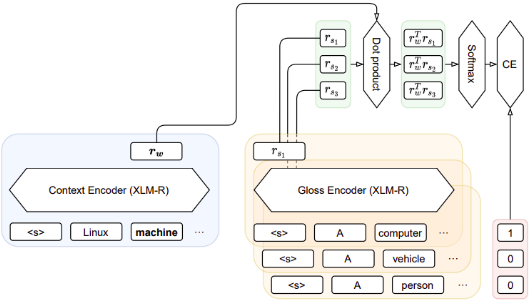
1. **Fine-tune** a model for sense disambiguation (English)



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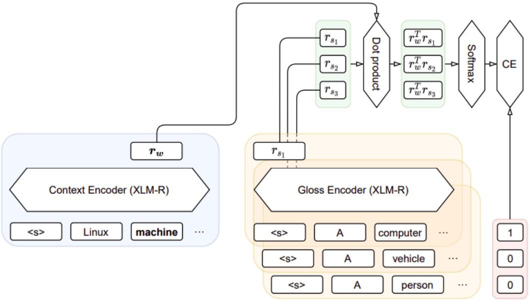
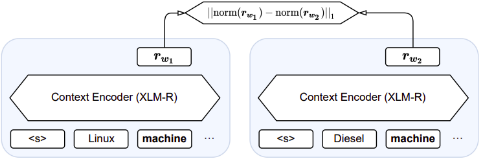
1. **Fine-tune** a model for sense disambiguation (English)
2. Use a fine-tuned model to compute similarity (Spanish)





Time-awareness

The methods we discussed so far are **time-oblivious** [Montanelli and Periti, 2023]

- No explicit information on time direction is used: corpora can be switched without changing of the model outputs
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- Time-oblivious methods can be re-used to track difference across other dimensions (topic, genre, etc.)
- Still, semantic shift detection could benefit from explicit knowledge of a time period

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- Temporal attention [Rosin and Radinsky, 2022]:

$$Attention(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

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- Adjusting input embeddings [Hofmann et al., 2021]

$$e = e' + o_t,$$

where e - token embedding at time point t, e' - time-agnostic representation, o_t - time-point embedding

Performance [Montanelli and Periti, 2023]

Ref.	SemEval English	SemEval German	SemEval Latin	SemEval Swedish	GEMS English	LivFC English	COHA English	LSCD Spanish	DURel German	SURel German	RSE Russian			NOR Norwegian	
	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_1-C_2	C_2-C_3	C_1-C_3	C_1-C_2	C_2-C_3
[Teodorescu et al., 2022]	-	-	-	-	-	-	-	ensemble APD 0.573	-	-	-	-	-	-	-
[Zhou and Li, 2020]	form-based CD 0.392	form-based CD 0.392	form-based CD 0.392	form-based CD 0.392	-	-	-	-	-	-	-	-	-	-	-
[Montariol et al., 2021]	sense-based AP + WD 0.456	sense-based AP + JSD 0.583	form-based CD 0.496	sense-based K-Means + WD 0.332	**sense-based** **AP + JSD** **0.510**	-	-	-	sense-based AP + JSD 0.712	-	-	-	-	-	-
[Periti et al., 2022]	sense-based AP + JSD 0.514*	-	sense-based APP + JSD 0.512*	-	-	-	-	-	-	-	-	-	-	-	-
[Pömsl and Lyapin, 2020]	ensemble APD 0.246	ensemble APD 0.725	ensemble APD 0.463	ensemble APD 0.546	-	-	-	-	**ensemble** **APD** **0.802**	**ensemble** **APD** **0.723**	-	-	-	-	-
[Rachinskiy and Arefyev, 2021]	-	-	-	-	-	-	-	-	-	-	ensemble APD 0.781	ensemble APD 0.803	ensemble APD 0.822	-	-
[Rachinskiy and Arefyev, 2022]	-	-	-	-	-	-	-	**sense** **APDP** **0.745**	-	-	-	-	-	-	-
[Rodina et al., 2021]	-	-	-	-	-	-	-	-	-	-	form-based PRT 0.557	sense-based AP + JSD 0.406	-	-	-
[Rosin et al., 2022]	form-based CD 0.467	-	form-based CD 0.512	-	-	**form-based** **TD** **0.620**	-	-	-	-	-	-	-	-	-
[Rosin and Radinsky, 2022]	**form-based** **CD** **0.627**	**form-based** **CD** **0.763**	**form-based** **CD** **0.565**	-	-	-	-	-	-	-	-	-	-	-	-
[Rother et al., 2020]	sense-based HDBSCAN 0.512	sense-based GMMs 0.605	sense-based GMMs 0.321	sense-based HDBSCAN 0.308	-	-	-	-	-	-	-	-	-	-	-
[Ryzhova et al., 2021]	-	-	-	-	-	-	-	-	-	-	ensemble regression 0.480*	ensemble regression 0.487*	ensemble regression 0.560*	-	
[Kudisov and Arefyev, 2022]	-	-	-	-	-	-	-	form-based APD 0.637	-	-	-	-	-	-	-
[Kutuzov, 2020]	form-based APD 0.605	form-based PRT 0.740	form-based PRT 0.561	**form-based** **APD** **0.610**	sense-based AP + JSD 0.456*	-	-	-	-	-	-	-	-	-	-
[Laicher et al., 2021]	form-based APD 0.571*	form-based CD 0.755*	-	form-based APD 0.602*	-	-	-	-	-	-	-	-	-	-	-
[Liu et al., 2021]	form-based CD 0.341	form-based CD 0.512	form-based CD 0.304	form-based CD 0.304	form-based CD 0.286	form-based CD 0.561	-	-	-	-	-	-	-	-	-
[Martinc et al., 2020c]	ensemble AP + JSD 0.361	ensemble AP + JSD 0.642	form-based CD 0.496	ensemble AP + JSD 0.343	-	-	-	-	-	-	-	-	-	-	-
[Giulianelli et al., 2020]	-	-	-	-	form-based APD 0.285*	-	-	-	-	-	-	-	-	-	-
[Giulianelli et al., 2022]	form-based APD 0.514	ensemble PRT 0.354	ensemble PRT 0.572	ensemble APD 0.397	-	-	-	-	-	-	ensemble APD + PRT 0.376	form-based APD 0.480	form-based APD 0.457	**ensemble** **APD + PRT** **0.394**	**ensemble** **APD** **0.503**
[Hu et al., 2019]	-	-	-	-	-	-	**sense-based** **MNS** **0.428***	-	-	-	-	-	-	-	-

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  - Though most interpretable methods are not necessary best-performing

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