Methods to represent natural language with application to conversational AI.

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	Emmanuel Vignon	IBM GBS

Today's Agenda

Conversational AI

FIGURE – Source : www.activechat.ai

FIGURE –
Source :https ://www.paymentsjournal.com/

Goal of Conversational AI [7, 15]

The long term goal of conversational AI is to build a superhuman computer that will mimic the property of human conversation and will be preferred to an ordinary human.

Specifics of Spoken Language

Caller	Utterance
A	um, did you do through a public school system or private ?
B	Yeah,
B	well, I went through private an until ninth grade.
A	Uh-huh,
A	did you notice a big difference ?
B	Oh, yeah,
B	a big difference.
A	Like in what sense ?

TABLE – Example of dialog taken from the Switchboard Dialog Act Corpus.

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Specifics of spoken dialog [15]

- *Disfluencies* (e.g "Uh-huh") [32]
- *Segmentation Issues* [1, 39]
- Lexical diversity, and grammatical complexity and accuracy. [6, 28]

Desirable qualities of conversational agents.[29]

- *Continual Learning :* continual learning enable the agent to adapt its behavior to new situations.
- *Engaging Content :* the agent needs to be able to carry and interesting and engaging conversation
- *Well behaved :* the agent can not generate offensive and toxic content

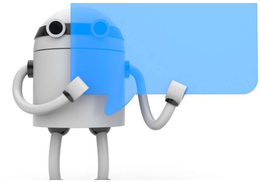

FIGURE – Source : https ://www.ladn.eu/

Aim of this thesis

We aim at textual learning representations useful for the conversational agent. Two types of problems arise :

- Understand the user's input (NLU)
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- RQ1 : *How to best represent inputs that contains text for NLU ? Can we build representations that take into account both the structural properties of the input and the target task i.e extracting the intends and associated information*.

- RQ2 : *How to best represent inputs that contains text for NLG ? Can we build representations that exhibit desirable topological properties (e.g invariance, disentanglement) for a specific sequence generation task ?*

RQ1 : Research Questions

RQ1 : *How to best represent inputs that contains text for NLU ?*

Can we build representations that take into account both the structural properties of the input and the target task i.e extracting the intends and associated information.

Three different scenarii :

- *The inputs are transcripts of spontaneous speech.* [a]
- *The inputs are interactions.* [b]
- *The input is multi-modal and comes from spontaneous speech.* [c]

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a. Work based on Dinkar(*) and Colombo(*) et al. EMNLP 2020

b. Work based on Colombo(*) and Chapuis(*) et al. AAAI 2020 and Chapuis(*) and Colombo(*) et al. Findings of EMNLP 2020

c. Work based on Garcia(*) and Colombo(*) et al. EMNLP 2019

RQ2 : Research Questions

RQ2 : *How to best represent inputs that contains text for NLG ?*

Can we build representations that exhibit desirable topological properties (e.g invariance, disentanglement) for a specific sequence generation task ?.

Two different tasks :

- *Sentence Generation with constant polarity.* [a]
- *Style Transfer.* [b]

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a. Work based on Jalazai(*) and Colombo(*) et al. NeurIPS2020
b. Work based on Colombo, Piantanida, Clavel. (Preprint)

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1. Context
   - Conversational AI
   - Research Questions (RQs)
2. RQ1 : *How to best represent inputs that contains text for NLU ?*
3. RQ2 : *How to best represent inputs that contains text for NLG ?*
4. Conclusions and Planning
5. References

Sequence labelling for conversational AI.

RQ1 : *How to best represent inputs that contains text for NLU ?*

Can we build representations that take into account both the structural properties of the input and the target task i.e extracting the intends and associated information.

Sequence Labellings

Importance of Sequence Labelling for CAs.

- **NLU** : Understand User's Query
- **NLG** : Controlled Generation over content, avoid generic response problem [36, 10].

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Speaker	**Utterance**	**Dialog Act (DA)**
A	Is there anyone who doesn't know Nancy ?	Yes/No Question
	Do you - Do you know Nancy ?	Question
B	Me ?	Question
	Mm-hmm	Backchannel
	I know Nancy	Yes/No Answer

TABLE – Example of Sequence Labelling with Dialog Act from [16]. Emotion Labels exhibit similar structure as DAs.

Sequence Labelling as an NMT problem [9]

SILICONE (Sequence labelling evaLuatIon benChmark fOr spoken laNguagE)

Limitations of current works on Sequence Labelling [20, 8, 18, 21] :

- Focus on type of label either **DA** or **Emotion**.
- Current methods require large corpora to train models from scratch.

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Corpus	$\|Train\|$	$\|Val\|$	$\|Test\|$	Utt.	$\|Labels\|$	Task	Utt./$\|Labels\|$
SwDA* [16]	1k	100	11	200k	42	DA	4.8k
MRDA* [31]	56	6	12	110k	5	DA	2.6k
DyDA$_a$	11k	1k	1k	102k	4	DA	25.5k
MT* [33]	121	22	25	36k	12	DA	3k
Oasis* [19]	508	64	64	15k	42	DA	357
DyDA$_e$[22]	11k	1k	1k	102k	7	E	2.2k
MELD$_s$*[27]	934	104	280	13k	3	S	4.3k
MELD$_e$*	934	104	280	13k	7	S	1.8k
IEMO[5]	108	12	31	10k	6	E	1.7k
SEM [25]	62	7	10	5,6k	3	S	1.9k

TABLE – Statistics of datasets composing SILICONE. E stands for emotion label and S for sentiment label ; * stands for datasets with available official split. Sizes of Train, Val and Test are given in number of conversations.

Models

Notations Each conversation C_i is composed of utterances u, i.e $C_i = (u_1, u_2, \ldots, u_{|C_i|})$ with $Y_i = (y_1, y_2, \ldots, y_{|C_i|})$ the corresponding sequence of labels. An utterance u_i is a sequence of words, i.e $u_i = (\omega_1^i, \omega_2^i, \ldots, \omega_{|u_i|}^i)$.
Hierarchical Encoder It is composed of two functions f^u and f^c, satisfying :

$$\mathcal{E}_{u_i} = f_\theta^u(\omega_1, \ldots, \omega_{|u_i|}) \tag{1}$$
$$\mathcal{E}_{C_j} = f_\theta^d(\mathcal{E}_{u_1}, \ldots, \mathcal{E}_{C_j}) \tag{2}$$

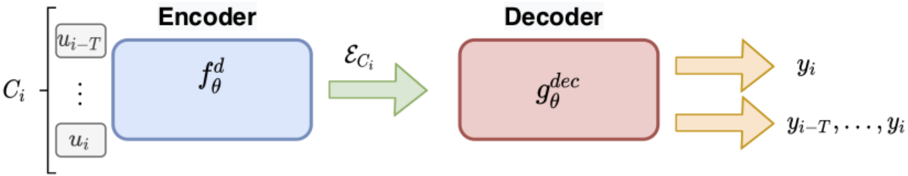

FIGURE – Model architecture for sequence labelling task. g_θ^{dec} represents the decoder layer.

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FIGURE – Model architecture for sequence labelling task. g^{dec}_θ represents the decoder layer.

We choose Transformer cells for f^u and f^c

Pretraining Objectives

Global hierarchical loss [30, 12]. The set of parameters θ is learnt by maximizing :

$$\mathcal{L}(\theta) = \underbrace{\lambda_u * \mathcal{L}^u(\theta)}_{\text{utterance level}} + \underbrace{\lambda_d * \mathcal{L}^d(\theta)}_{\text{dialog level}} \tag{3}$$

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$$\mathcal{L}^u_{\mathtt{MLM}}(\theta, u_i) = \mathbb{E}\left[\sum_{t \in m^{u_i}} \log(p_\theta(\omega^i_t | \tilde{u}_i))\right] \tag{4}$$

where $\tilde{u}_i$ is the corrupted utterance, $m^{u_i}_j \sim unif\{1, |u_i|\} \ \forall \ j \in [1, p_\omega]$

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Pretaining Corpora : OpenSubtitles [23], ∼54M conversations and ∼270M utterances

Overall Results

- **Emotion and Sentiment Labels are noisier than DA**.
- Pretrained model achieves better results.

	Avg	SwDA	MRDA	$\mathrm{DyDA}_{\mathrm{DA}}$	MT	Oasis	DyDA_e	MELD_s	MELD_e	IEMO	SEM
BERT-4layers	70.4	77.8	90.7	79.0	88.4	66.8	90.3	55.3	53.4	43.0	58.8
$\mathcal{HR}$	69.8	77,5	90,9	80,1	82,8	64,3	91.5	59,3	59.9	40.3	51.1
$\mathcal{HT}(\theta^{u,d}_{MLM})$	73.3	**79.3**	92.0	80.1	90.0	68,3	92.5	62.6	59.9	42.0	66.6
$\mathcal{HT}(\theta^{d}_{GAP})$	71.6	78.6	91.8	78.1	89.3	64.1	91.6	60.5	55.7	42.2	63.9

TABLE – Performances of different encoders when decoding using a MLP on SILICONE. The datasets are grouped by label type (DA vs E/S) and ordered by decreasing size.

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TABLE – Results on SILICONE for pre-trained BERT models.

- **Source** of the pretraining data matters.

Conclusion and Perspectives

Summary of our contributions

1. New Benchmark for Sequence Labeling Tasks (`SILICONE`)
2. Preprocess and pretrained on a large collection of Spoken Dialog (OpenSubtitles)
3. Explore New Pretraining Objectives
4. Hierarchical Transformers Based Encoder (Reduced Parameters and GPUs)

Future Work and Perspectives

1. Explore Sequence Labelling Tasks In a Multilingual Setting

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Learning A Disentangled Representation.

RQ2 : *How to best represent inputs that contains text for NLG ?*

Can we build representations that exhibit desirable topological properties (e.g invariance, disentanglement) for a specific sequence generation task ?.

Motivations

Importance of Disentangled Representations

- Visual Reasonning [34].
- Robust and Fair classification [2].
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Learning Disentangled representations.

Learn a model $\mathcal{M} : \mathcal{X} \to \mathcal{R}^d$
Goal : Output vector has to retain as much as possible information of the original content from the input sentence but as little as possible about the undesired attribute Y.
Assumption : $Y \in \mathcal{Y}$ is discrete.

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We focus on applications **textual style transfer**.
Goal : Disentangled content and polarity (style).

Related Work

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Limitation of Adversarial Losses

- Disentanglement is not perfect [13].
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Related Work

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Mutual Information Given two random variables Z and Y, the MI is defined by

$$I(Z;Y) = \mathbb{E}_{ZY}\left[\log \frac{p_{ZY}(Z,Y)}{p_Z(Z)p_Y(Y)}\right], \tag{6}$$

where p_{ZY} is the joint pdf and p_Z and p_Y are the marginal pdfs.

Contributions and Methods

Contributions

- A novel objective to train disentangled representations from attributes which include a new variational estimate of the MI
- Applications and numerical results and we demonstrate that the aforementioned surrogate is better suited than the widely used adversarial losses

General Loss to Minimize

$$\mathcal{L}(f_{\theta_e}) \equiv \underbrace{\mathcal{L}_{down.}(f_{\theta_e})}_{\text{downstream task}} + \lambda \cdot \underbrace{I(f_{\theta_e}(X); Y)}_{\text{disentangled}}, \qquad (7)$$

$\mathcal{L}_{down.}$ represents a downstream specific (target task) loss
λ is a meta-parameter
f_{θ_e} is the encoding function

Estimating The MI

Computing the MI is a long standing challenge [3, 17, 26].

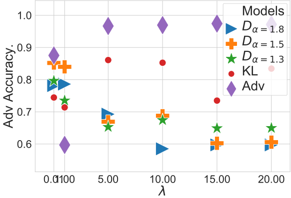
Variational upper bound on MI

Let (Z, Y) be an arbitrary pair of RVs with $(Z, Y) \sim p_{ZY}$ according to some underlying pdf, and let $Q_{\widehat{Y}|Z}$ be a conditional variational distribution on the attributes satisfying $P_{ZY} \ll P_Z \cdot Q_{\widehat{Y}|Z}$, i.e., absolutely continuous. Then, we have that

$$I(Z;Y) \leq \mathbb{E}_Y \left[-\log \int_{R^d} Q_{\widehat{Y}|Z}(Y|z) P_Z(dz) \right] + \mathbb{E}_{YZ} \left[\log Q_{\widehat{Y}|Z}(Y|Z) \right] + D_\alpha \left(P_{ZY} \| P_Z Q_{\widehat{Y}|Z} \right) \tag{8}$$

where $D_\alpha \left(P_{ZY} \| P_Z Q_{\widehat{Y}|Z} \right) = \frac{1}{\alpha - 1} \log \mathbb{E}_{ZY}[R^{\alpha-1}(Z, Y)]$ denotes the Renyi divergence and $R(z, y) = \frac{P_{Y|Z}(y|z)}{Q_{\widehat{Y}|Z}(y|z)}$, for all pairs $(z, y) \in \mathrm{Supp}(P_{ZY})$.

Application to Textual Style Transfer



Yelp corpus : Review from Yelp. The task consists in transferring a binary sentiment (positive/negative) [37, 24].

FIGURE – Disentanglement of the representations learnt by the encoder f_{θ_e} when the model is trained on a binary sentence generation task.

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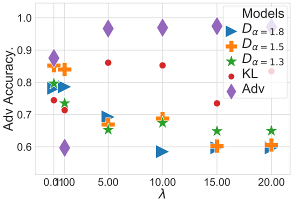

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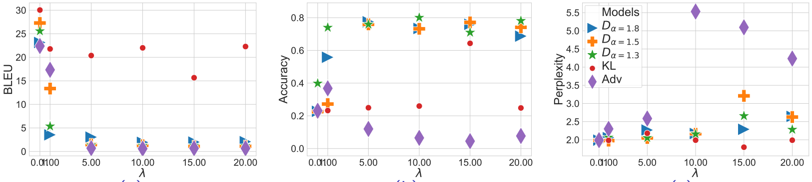

(a) (b) (c)

FIGURE – Numerical experiments on binary style transfer. Quality of generated sentences are evaluated using BLEU (6a) ; style transfer accuracy (6a) ; sentence fluency (6c).

Application to Textual Style Transfer

	Input	**It's freshly made, very soft and flavorful.**
0.1	Adv	it's crispy and too nice and very flavor.
	KL	it's a huge, crispy and flavorful.
	$D_{\alpha=1.3}$	it's hard, and the flavor was flavorless.
	$D_{\alpha=1.5}$	it's very dry and not very flavorful either.
	$D_{\alpha=1.8}$	it's a good place for lunch or dinner.
	Input	it's freshly made, very soft and flavorful.
1	Adv	it's not crispy and not very flavorful flavor.
	KL	it's very fresh, and very flavorful and flavor.
	$D_{\alpha=1.3}$	it's not good, but the prices are good.
	$D_{\alpha=1.5}$	it's not very good, and the service was terrible.
	$D_{\alpha=1.8}$	it was a very disappointing experience and the food was awful.
	Input	it's freshly made, very soft and flavorful.
10	Adv	i hate this place.
	KL	it's a little warm and very flavorful flavor.
	$D_{\alpha=1.3}$	it was a little overpriced and not very good.
	$D_{\alpha=1.5}$	it's a shame, and the service is horrible.
	$D_{\alpha=1.8}$	it's not worth the $ NUM.

TABLE – Sequences generated by the different models on the binary sentiment transfer task.

Conclusion and Perspectives

Summary of our contributions

1. New Estimate of MI based on an upper Bound
2. New method capable of learning disentangled textual representation
3. Better Trade off in Fair Classification
4. There is no free-lunch for sentence generation tasks : transferring style is easier with disentangled representations, but removes important information about the content.

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Conclusion and Perspectives

On going work on RQ1

1. **Multilingual DAs**. Learning more general encoders that can adapt to different languages. Improved version of Colombo(*), Chapuis(*) et al *AAAI 2020* and Chapuis(*), Colombo(*) et al. *Findings of EMNLP 2020*
2. **Learning Better Fusion Model**. Improved version of Garcia(*), Colombo(*) et al. *EMNLP 2019*.

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Follow Up Work (RQ1)

1. **Disfluency**. Planned follow up work on Dinkar(*), Colombo(*) et al. *EMNLP 2020*.

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Futur Work on (RQ2)

1. **New evaluation metrics**. An inherent problem that arise in NLG is the lack of evaluation metric relying on continuous representations. I believe we can do better than BertScore [38].

Conclusion and Perspectives

Month	Planned Work	Conference Paper Deadlines
November	Multi Modal	
December	Multi Lingual	NAACL
January		
February		ICML
March	Metric	ACL
April		ECML
May	Disfluency	NeurIPS, EMNLP
June		
July	Thesis Redaction	
August		
September		ICLR, AAAI
October		
November	PhD Defense	NAACL

TABLE – Planning of the remaining year of my PhD thesis.

Thank You!

Results presented in this report are the fruit of collaborations with my great PhD advisors Chloe Clavel, Giovanna Varni, Emmanuel Vignon **as well as with amazing senior researchers :** Pablo Piantanida, Matthieu Labeau, Matteo Manica, Florence D'Alche-Buc, Anne Sabourin, Eric Gaussier ,Slim Essid, Chouchang Jack Yang **and state of the art PhD students :** Tanvi Dinkar, Emile Chapuis, Alexandre Garcia **and last but not least** Hamid Jalalzai**. I am thankful to all of them for the hard-work and the fun moments we had and we will have.**

Today's Agenda

References I

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Back-up Slides

Modelling Disfluencies

RQ1 : *How to best represent inputs that contains text for NLU ?*

Can we build representations that take into account both the structural properties of the input and the target task i.e extracting the intends and associated information.

Introduction

- Spoken language is rarely fluent, filled with disfluencies.
- Fillers : disfluencies filling a pause in an utterance or conversation, "um" or "uh" in English.
- Meanings of fillers : Contextual, dependent on the perception of the listener.
- Feeling of another's knowing (FOAK) (Brennan Williams, 1995), perception of confidence.
- Despite rich linguistic literature, fillers SLU typically considered noise !

FIGURE – Source : Jorge Cham, www.phdcomics.com

Aim of this work

- O1 : Fillers play an important role in spoken language, should not be removed as noise.
- O2 : Fillers play an important role in the listener's perception of the speaker's expressed confidence (FOAK).
- Experimental validation of O1,O2, without handcrafting features.
- Efficiently represent and study informativeness of fillers using SOTA models.

Dataset

- POM dataset (Park et al., 2014), spontaneous speech, movie review videos. Speakers record videos of themselves giving a movie review.
  - Annotators : "How confident was the speaker ?"
  - Annotations of fillers and confidence available.
- Filler count high (4%), inter-annotator agreement confidence high (Kripps alpha = 0.73).
- Annotator were not asked to pay attention to the speaker's use of fillers.
- Monologues, dialogue related disfluencies (such as backchannels) are not present.

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O1 : Fillers play an important role in spoken language

- A language modelling task, using BERT, same MLM objective.
- Each experiment : token representation strategy (TR) and a pre-processing strategy (PS).

PS1 : Fillers removed	PS3 : Fillers kept
TR1 : No special treatment	TR2 : Special token for each

  - Raw (um) Things that (uh) you usually wouldn't find funny.
  - TR1 ['um', 'things', 'things', 'that', 'uh'...]
  - TR2 ['[FILLER-UM]', 'things', 'that', '[FILLER-UH]'...]
- Optionally fine-tune BERT for each PS and TR, using MLM.

O1 : Results

- Adding fillers, both with and without fine-tuning, model with lower perplexity.

Language Modelling task		Perplexity
w/o fine-tuning	PS1 : Fillers removed (Training + inference)	22
	PS3 : Fillers kept	20
w fine-tuning	PS1 : Fillers removed	5.5
	PS3 : Fillers kept	4.6

- Fixing PS3 as strategy, TR1 best. Better to keep the existing representations.

Best Token Representation		Perplexity
PS3	TR1 : No treatment	4.6
	TR2/3 : Treatment	4.7

- Interestingly, BERT unable to distinguish between two fillers.

O2 : Results

- Downstream confidence prediction task, informative.
  - Adding a Multi-Layer Perceptron (MLP) on top of a BERT.
  - Same pre-processing PS as before, fixed token rep TR1.
  - Optionally fine-tuned using the MLM.
  - Mean Squared Error (MSE) loss.
- Results
  - PS3 (Fillers kept in training+inference) outperform other PS, both with/without MLM fine tune.
  - Fillers, discriminative feature in confidence prediction.

Confidence Prediction task		MSE
w/o MLM	PS1 : Fillers removed	1.47
	PS3 : Fillers kept	1.30
w MLM	PS1 : Fillers removed	1.32
	PS3 : Fillers kept	1.24

Takeaway

- Fillers, improve results when working with contextualised word embeddings : LM, in spoken language, fillers leveraged to reduce uncertainty of BERT.
  - Unexpected, as intuitively, perplexity reduction as sentence simplified.
  - BERT, representation of fillers already exist.
- Downstream task of confidence/FOAK prediction.
  - Fillers, discriminative feature in confidence prediction.
  - Validation on spontaneous speech corpora.
- Unsupervised way of studying their informativeness.
- Future work : Acoustic representation, pre-trained representations.

Representing Multimodal Input for fine-grained opinion mining.

RQ1 : *How to best represent inputs that contains text for NLU ?*

Can we build representations that take into account both the structural properties of the input and the target task i.e extracting the intends and associated information.

Multimodal Opinion Mining

Definition of an opinion : The expression of opinions is an evaluation towards an object. The expression of such evaluations can be summarised by the combination of three components :

- a source (mainly the speaker) expressing a statement
- a target identifying the entity evaluated
- a polarised expression

FIGURE – Frames illustrating negative, positive or neutral opinions

Data Presentation : Garcia et Al. 2019

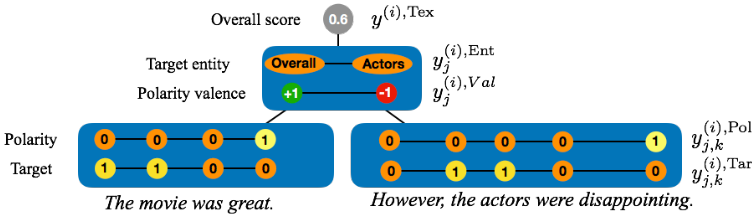

FIGURE – Structure of an annotated opinion

- *Token-level labels* are represented by a sequence of 2-dimensional binary label vectors
- *Sentence*-level labels carry 2 pieces of information : (1) the categorization of the target *entities*, (2) the sentence polarity (*Positive*, *Negative*, *Neutral/Mixed* and *None*).
- *Text*-level labels a continuous score summarizing the overall rating.

Motivations

In this work we show :

- The redundancy of the opinion information contained at different granularities can be leveraged improved opinion predictors.
- We propose several generic curriculum strategies to improve learning process in a MT setting.
- We demonstrate that jointly predicting entities and opinion helps to achieve better results

Background on Multi-modal Learning

When working with multimodal data several challenges need to be solved :

- **Representation** : Represent and summarize multimodal data in away that exploits the complementarity and redundancy.
- **Alignment** : Identify the direct relations between (sub)elements from two or more different modalities.
- **Fusion** : To join information from two or more modalities to perform a prediction task
- **Co-Learning** : Transfer knowledge between modalities, including their representations and predictive models.

Multi-Task Learning (1/3)

Based on these representations, we define a set of losses, $l^{(\text{Tok})}, l^{(\text{Sent})}, l^{(\text{Tex})}$ dedicated to measuring the similarity of each substructure prediction, $\hat{\mathrm{y}}^{(\text{Tok})}, \hat{\mathrm{y}}^{(\text{Sent})}, \hat{\mathrm{y}}^{(\text{Tex})}$ with the ground-truth.

$$l^{(Tok)}(\mathrm{y}^{\text{Tok}}, \hat{\mathrm{y}}^{\text{Tok}}) = -\frac{1}{2}\sum_i ((\mathrm{y}_i^{Pol}\log(\hat{\mathrm{y}}_i^{Pol}) + \quad \mathrm{y}_i^{Tar}\log(\hat{\mathrm{y}}_i{}^{Tar})),$$

$$l^{(Sent)}(\mathrm{y}^{Sent}, \hat{\mathrm{y}}^{Sent}) = -\frac{1}{2}\sum_i (\mathrm{y}_i^{\text{Ent}}\log(\hat{\mathrm{y}}_i^{\text{Ent}}) + \quad \mathrm{y}_i^{\text{Val}}\log(\hat{\mathrm{y}}_i^{\text{Val}})),$$

$$l^{(Tex)}(y^{\text{Tex}}, \hat{y}^{\text{Tex}}) = (y^{\text{Tex}} - \hat{y}^{\text{Tex}})^2,$$

The loss we optimise l, is a convex combination of these different task at each granularity level : $t \in \text{Tasks} = \{Tok, Sent, Tex\}$ weighted according to a set of task weights λ_t :

$$l(\mathrm{y}, \hat{\mathrm{y}}) = \frac{\sum_{t \in \text{Tasks}} \lambda_t l^{(t)}(\mathrm{y}^t, \hat{\mathrm{y}}^t)}{\sum_{t \in \text{Tasks}} \lambda_t}, \ \forall \lambda_t \geq 0. \tag{9}$$

Example of Strategies

In order to gradually guide the model from easy tasks to harder ones, λ_t is defined as function of the number of epochs of the form $\lambda_t^{(n_{\text{epoch}})} = \lambda_{\max} \frac{\exp\left((n_{\text{epoch}} - Ns_t)/\sigma\right)}{1+\exp\left((n_{\text{epoch}} - Ns_t)/\sigma\right)}$

- Strategy 1 (S1) consists in optimizing the different objectives one at a time from the easiest to the hardest. The underlying idea is that the low level labels are only useful as an initialization point for higher level ones.

- Strategy 2 (S2) consists in adding sequentially the different objectives to each other from the easiest to the hardest. This strategy relies on the idea that keeping a supervision on low level labels has a regularizing effect on high level ones.

Model Architectures (1/3)

From a general perspective, a hierarchical opinion predictor is composed of 3 functions $g^{\text{Tex}}, g^{\text{Sent}}, g^{\text{Tok}}$ encoding the dependency across the levels :

$$
\begin{aligned}
h_{j,k}^{(i),\text{Tok}} &= g_{\theta^{\text{Tok}}}^{\text{Tok}}(x_{j,:}^{(i),\text{Tok}}), & \hat{y}^{(i),\text{Tex}} &= \sigma^{\text{Tex}}(W^{\text{Tex}} h^{(i),\text{Tex}} + b^{\text{Tex}}),\\
h_j^{(i)^{\text{Sent}}} &= g_{\theta^{\text{Sent}}}^{\text{Sent}}(h_{j,:}^{(i)^{\text{Tok}}}), & \hat{y}_j^{(i),\text{Sent}} &= \sigma^{\text{Sent}}(W^{\text{Sent}} h_j^{(i)^{\text{Sent}}} + b^{\text{Sent}}),\\
h^{(i)^{\text{Tex}}} &= g_{\theta^{\text{Tex}}}^{\text{Tex}}(h_:^{(i)^{\text{Sent}}}). & \hat{y}_{j,k}^{(i),\text{Tok}} &= \sigma^{\text{Tok}}(W^{\text{Tok}} h_{j,k}^{(i),\text{Tok}} + b^{\text{Tok}})
\end{aligned}
$$

Choice of architectures for g_θ

- **Bidirectional Gated Recurrent Units (BiGRU)**
- **The Multi-attention Recurrent Network (MARN)** extends the traditional Long Short Term Memory.
- **Memory Fusion Networks (MFN)** are a second family of multi-view sequential models built upon a set of LSTM.

Several pooling strategies available (Last state representation, attention based sequence summarization)

Experiment 1 : Which architecture provides the best results on the task of fine grained opinion polarity prediction ?

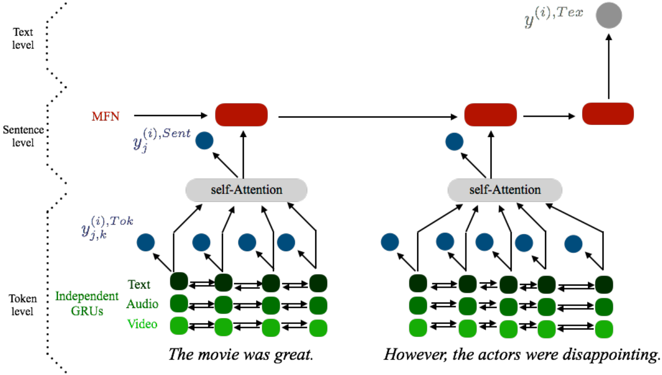

FIGURE – Example of architecture

Experiment 1 : Which architecture provides the best results on the task of fine grained opinion polarity prediction ?

	$\lambda_{Tok} = \lambda_{Sent} = 0$: no fine grained supervision				
Model / Metric	BiGRU	Ind BiGRU + att	MARN	MFN	Av Emb
MAE *Text*	0.35	0.38	0.29	0.32	**0.17**
	λ_{Tok},λ_{Sent} : Supervision at the token, sentence and review levels				
$\mu F1$ *Tokens*	0.90	**0.93**	0.90	0.89	X
$\mu F1$ *Sentence*	0.68	**0.75**	0.52	0.47	X
MAE *Text*	0.16	0.15	0.35	0.37	X

TABLE – Scores on sentiment label

Experiment 1 : Which architecture provides the best results on the task of fine grained opinion polarity prediction ? (2/2

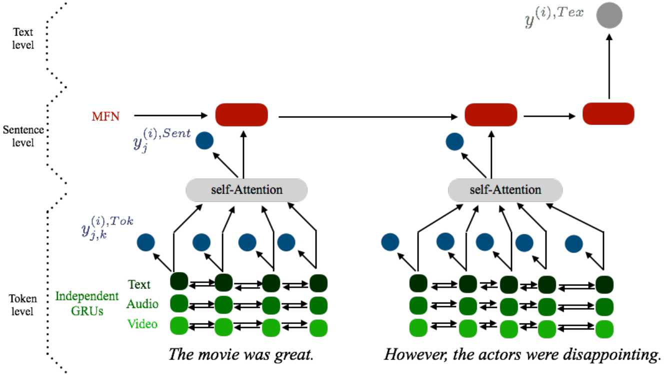

FIGURE – Best architecture selected during the Experiment 1

Experiment 2 : What is the best strategy to take into accou

multiple levels of opinion information ?

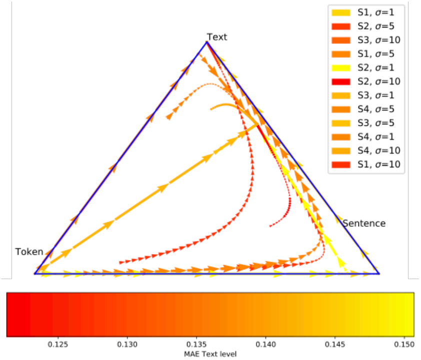

FIGURE – Path of the weight vector in the simplex triangle for the different tested strategies

Experiment 3 : Is it better to jointly predict opinions and entities ?

	Polarity labels	Entity labels	Polarity + entities
F1 polarity tokens	0.93	X	0.93
F1 polarity valence	0.75	X	0.75
F1 entities tokens	X	0.97	0.97
F1 entities Entities	X	Table **??**	Table **??**
MAE score review level	0.14	0.38	0.14

TABLE – Joint and independent prediction of entities and polarities

	Entity	Entity + Polarity	Value Count
Overall	0.71	**0.73**	1985
Actors	**0.65**	**0.65**	493
Screenplay	0.60	**0.63**	246
Atmosphere and mood	0.62	**0.64**	151
Vision and special effects	**0.62**	0.58	154

TABLE – F1 score per label for the top entity categories annotated at the sentence level (mean score averaged over 7 runs), value counts are provided on the test set.

Takeaways & Perspective

In this work we show :

- The redundancy of the opinion information contained at different granularities can be leveraged improved opinion predictors.
- We propose several generic curriculum strategies to improve learning process in a MT setting.
- We demonstrate that jointly predicting entities and opinion helps to achieve better results

Future work will explore the use of *structured output learning* methods dedicated to the opinion structure.

Learning A Dilation Invariant Representation.

RQ2 : *How to best represent inputs that contains text for NLG ?*

Can we build representations that exhibit desirable topological properties (e.g invariance, disentanglement) for a specific sequence generation task ?.

Motivations

Label Invariant Sentence Generation with Guarantees.

$$g\left(h_\lambda(\varphi(x))\right) = g\left(\varphi(x)\right). \tag{10}$$

$\forall \lambda \geq 1$ For an input sentence x, the embedding function is called φ and g a classifier.

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Limitations of Current Embeddings ELMo, BERT, XLNet trained on massive corpora show convenient properties but they do not fit our problem.

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Limitations of Current Embeddings ELMo, BERT, XLNet trained on massive corpora show convenient properties but they do not fit our problem.
Dilation Invariance : h_λ is chosen as the homothety with scale factor λ, $h_\lambda(x) = \lambda x$.

Definitions

Extrems

A r.v X is *extreme*, if $X \in \mathbb{R}_+ . \big(X > t, \text{ for some} t \geq 0.\big)$

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Heavy Tailed Distribution

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Example

- Exponential(λ) : $\mathbb{P}(X > t) = e^{-\lambda t}$ is not heavy tailed (choose $c < \lambda$)
- Pareto(α) : $\mathbb{P}(X > t) = 1/t^{\alpha}$ is heavy tailed.

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Jalalzai et al. NIPS 2018

There exists a classifier $g^{\star}_{\infty}$ depending on the pseudo-angle $\Theta(x) = \|x\|^{-1}x$ only, that is $g^{\star}_{\infty}(x) = g^{\star}_{\infty}\big(\Theta(x)\big)$, which is asymptotically optimal in terms of classification risk. The angle $\Theta(x)$ belongs to the positive orthant of the unit sphere.

Learning a Heavy-Tailed Representation (LHTR)

We suppose that :

- We are given a labelled dataset (x_i, y_i)
- We are given an embedding (in our case BERT)
- We are given an heavy-tailed distribution (Multivariate Logistic).

We learn φ using an adversarial approach.

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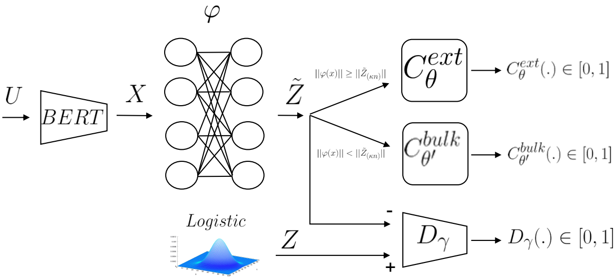
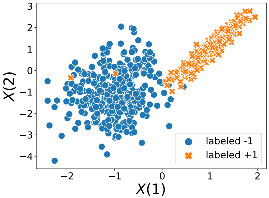


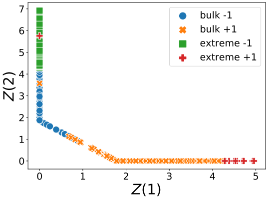
FIGURE – Pipeline to learn an heavy-tailed representation

Toy Datasets : bivariate data

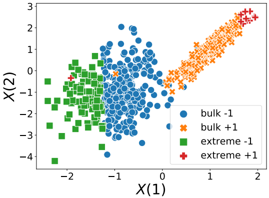
We begin with 2D Toy Datasets



(a) Input bivariate data



(b) Latent Space learnt by φ.



(c) Input Space with extremes from each class selected in the input space

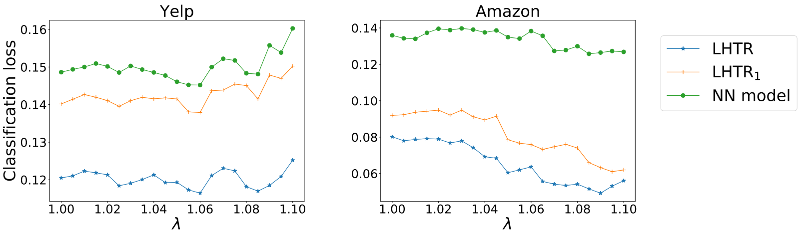
Dilation Invariance

C^{ext} solely depends on $Z/||Z||$!

Binary Classification in Extremes

Textual Datasets with binary rating

- Yelp : 1,450k reviews
- Amazon : 231k reviews



Figure

`NN model` is a MLP trained on BERT. For **`LHTR`**$_1$ a single MLP (C) is trained on φ. **`LHTR`**trains two separate MLP C^{ext} and C^{bulk} on φ.

Putting Pieces Together

Dilation Invariance

If Z is extreme, C^{ext} solely depends on $Z/||Z||$ implies that
$C^{\text{ext}}(\lambda Z) = C^{\text{ext}}(Z), \qquad \forall \lambda > 1.$

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Any dilation of a sample from the latent space will share the same label.

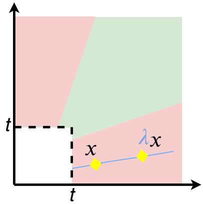

FIGURE – Illustration of dilation invariance property. Red region lies for $y = 1$ and green region for $y = 0$

Label Preserving Data Augmentation in Extremes

Label Invariant Sentence Generation with Guarantees.

$$g\left(h_\lambda(\varphi(x))\right) = g\left(\varphi(x)\right). \tag{11}$$

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Use a frozen φ for sentence generation using a seq2seq model.

input	all of the tapas dishes were delicious !
$\lambda = 1$	all the tapas was delicious.
$\lambda = 1.1$	all tapas dishes were delicious !
$\lambda = 1.3$	all the tapas dishes were delicious !
$\lambda = 1.5$	the tapas were great !
input	there was hardly any meat.
$\lambda = 1$	there was almost no meat.
$\lambda = 1.1$	there was practically no meat.
$\lambda = 1.3$	there was almost no meat.
$\lambda = 1.5$	there was no meat.
input	i 'm not eating here !
$\lambda = 1$	i don't eat here.
$\lambda = 1.1$	i don't eat here !
$\lambda = 1.3$	i'm not going to eat here !
$\lambda = 1.5$	i will never going to eat here !