Generative models for natural language inference

DGM4NLP

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Outline

Introduction

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  $T \rightarrow H$

T: The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure.
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- Physicians are trained in medicine to recognise and treat a disease.

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RTE can be **framed** as a classification problem, where the entailment relations are the classes, and the RTE benchmark provides the essential evidence to build a **supervised binary classifier** (Dagan et al., 2010)

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- We can frame natural language processing tasks as recognition.
  Input as T and generated output as H.

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> T/Q: Arabic, for example, is used densely across North Africa and from the Eastern Mediterranean to the Philippines, as the key language of the Arab world.
> H/A: Arabic is the primary language of the Philippines.

Summarisation

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> T/S1: Google and NASA announced a working agreement, Wednesday, that could result in the Internet giant building a complex of up to 1 million square feet on NASA-owned property, adjacent to Moffett Field, near Mountain View.
>
> H/S2: Google may build a campus on NASA property.

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- determine that "A purchased by B" implies "B acquires A".

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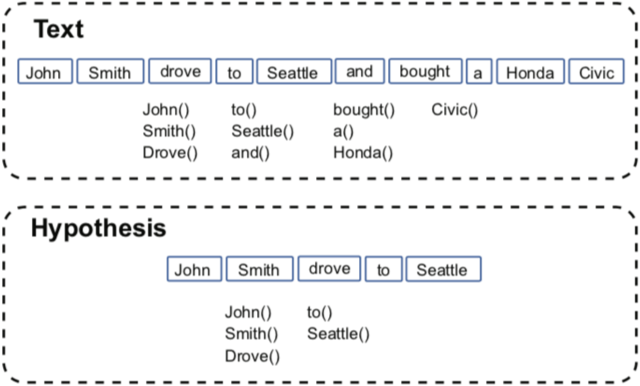
- The representation (e.g. words, syntax, semantics) of the T-H pair that is used to extract features to train a supervised classifier.

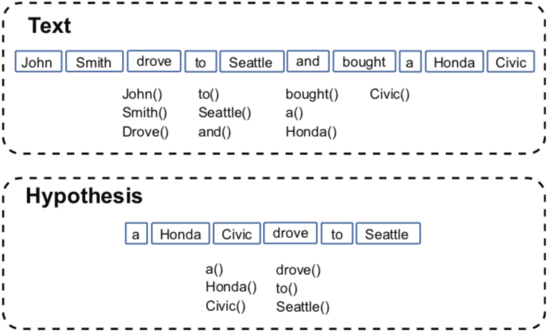
Lexical level

- Every assertion (word) in the representation of H is contained in the representation T.



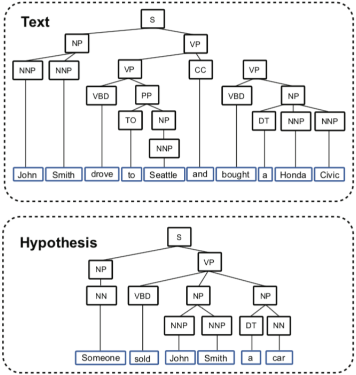
Lexical level

- H and T sentences encode aspects of underlying meaning that cannot be captured by the purely lexical representation.



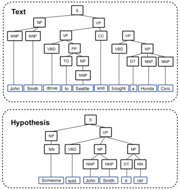
Structural level

- Syntactic structure provides cues for the underlying meaning of a sentence.



Structural level

- If T contains the same structure (i.e, dependency edges), the system will predict TRUE and otherwise FALSE.



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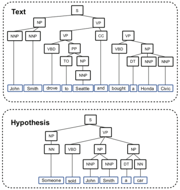
- “John” and “drove,” but the two words are **separated** by a sequence of dependency edges.



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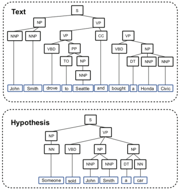
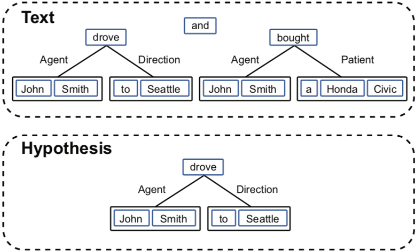
- Given the expressiveness of the dependency representation, many possible sequences of edges that could represent connection, and many other sequences that do not.



Semantic level

- Semantic role labelling, grouping of words into "arguments" (entity such as a person or place) and "predicates" (a predicate being a verb representing the state of some entity).



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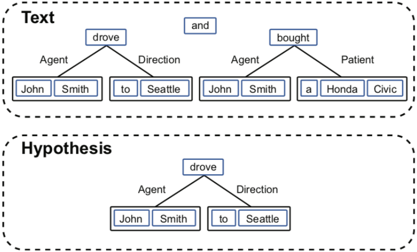

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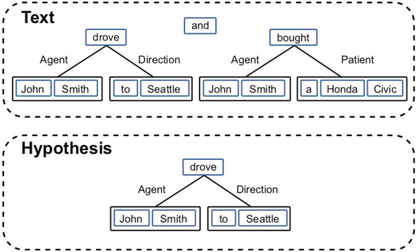
- "John" is an argument of the predicate "drove"



Knowledge Acquisition for RTE

- T: The U.S. citizens elected their new president Obama.
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- Assumed **background knowledge**: "U.S. presidents should be naturally born in the U.S."

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- But also meaning implication between more complex structures than just lexical terms.
  X *causes* Y $\rightarrow$ Y *is a symptom of* X

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- Wikipedia articles for identifying **is a** relations.
  Jim Carrey → actor

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- X solves Y
  Y is solved by X
  X finds a solution to Y

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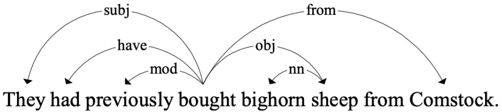

(a)	$\boxed{\text{N:subj:V}} \leftarrow \text{buy} \rightarrow \boxed{\text{V:from:N}}$	(*X* buys something from *Y*)
(b)	$\boxed{\text{N:subj:V}} \leftarrow \text{buy} \rightarrow \boxed{\text{V:obj:N}}$	(*X* buys *Y*)
(c)	$\boxed{\text{N:subj:V}} \leftarrow \text{buy} \rightarrow \boxed{\text{V:obj:N}} \rightarrow \text{sheep} \rightarrow \boxed{\text{N:nn:N}}$	(*X* buys *Y* sheep)
(d)	$\boxed{\text{N:nn:N}} \leftarrow \text{sheep} \leftarrow \boxed{\text{N:obj:V}} \leftarrow \text{buy} \rightarrow \boxed{\text{V:from:N}}$	(*X* sheep is bought from *Y*)
(e)	$\boxed{\text{N:obj:V}} \leftarrow \text{buy} \rightarrow \boxed{\text{V:from:N}}$	(*X* is bought from *Y*)

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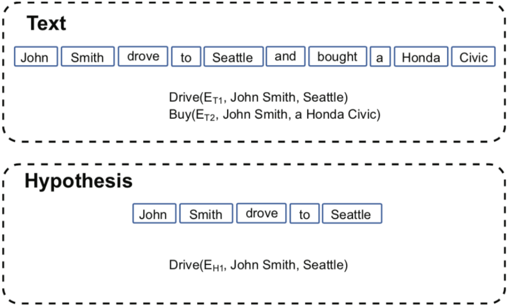

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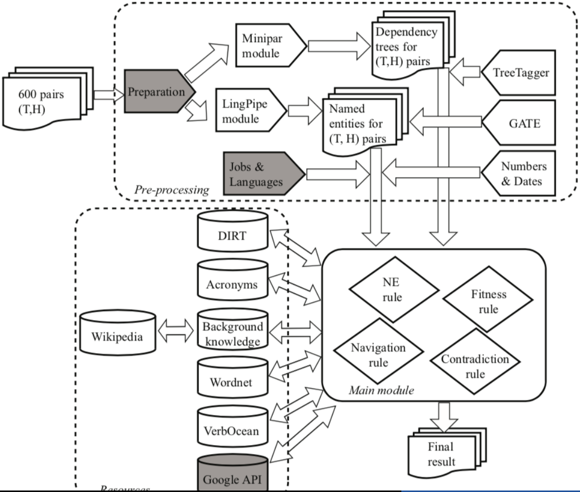
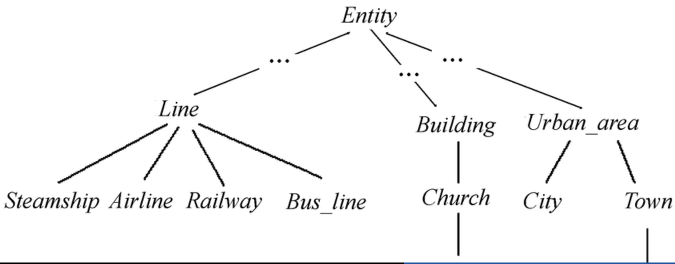


Similarity-based approaches

- Pair with a strong similarity score holds a positive entailment relation.



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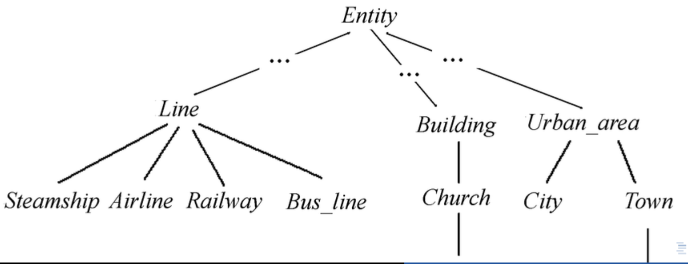

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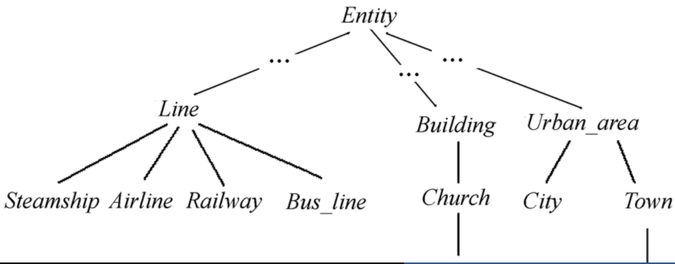

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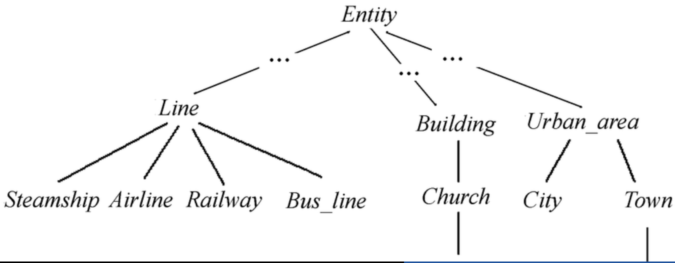
- Similarity scores computed from different linguistic levels. The goal is to find complementary features.



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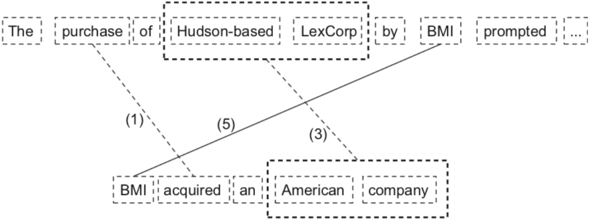

- (1,purchase,acquired)
  (3,Hudson-based LexCorp, American company),
  (5,BMI,BMI)

- $\rho_4 = \text{purchase of } \boxed{\text{X}} \text{ by } \boxed{\text{Y}} \;\rightarrow\; \boxed{\text{Y}} \text{ acquired } \boxed{\text{X}}$
- $\rho_5 = \boxed{\text{Z:Noun}} \text{ of } \boxed{\text{X}} \text{ by } \boxed{\text{Y}} \;\rightarrow\; \boxed{\text{Y}}\, \boxed{\text{Z:Verb}}\, \boxed{\text{X}}$

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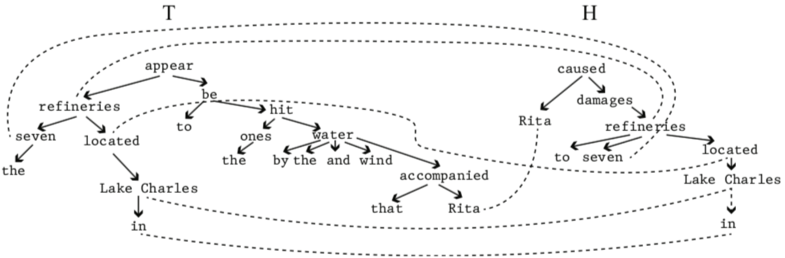

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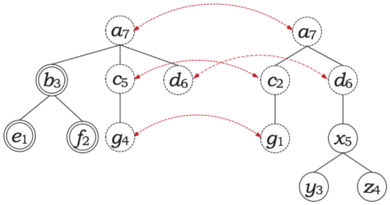

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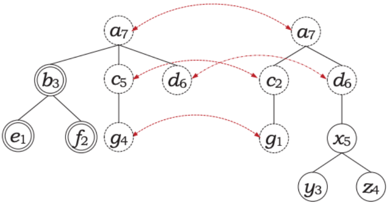

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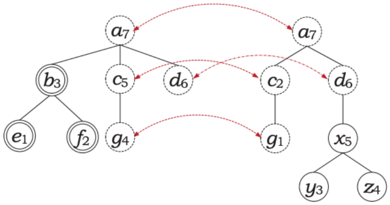

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- RTE-4 and RTE-5 increase the difficulty by adding irrelevant signals (additional words, phrases, and sentences).

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- Premise: A soccer game with multiple males playing. Hypothesis: Some men are playing a sport.

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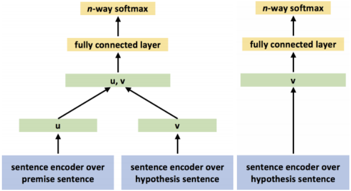
- T: 8 million in relief in the form of emergency housing.
  H: The 8 million dollars for emergency housing was still not enough to solve the problem.
  Government

Drawbacks



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Entailment	There are **at least** three **people** on a loading dock.
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Contradiction	A woman is **not** taking money for any of her sticks.

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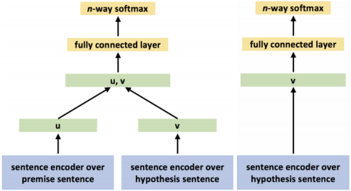

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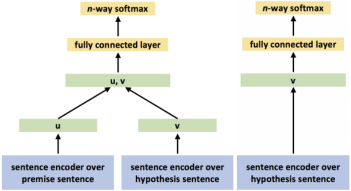

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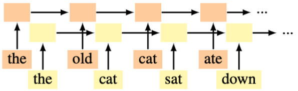
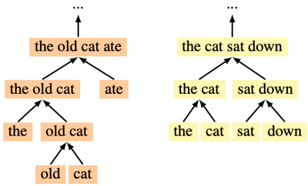
- Neutral: Modifiers (tall, sad, popular) and superlatives (first, favorite, most)
- Contradiction: Negation words, nobody, no, never and nothing

Neural Network Models

- Embeddings like glove or elmo, for fine tuning.



(a) A conventional sequence-based RNN for two sentences.



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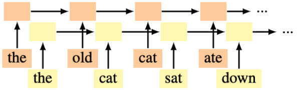

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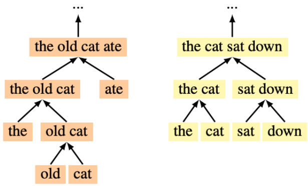

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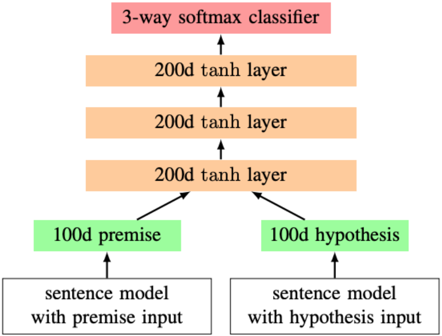
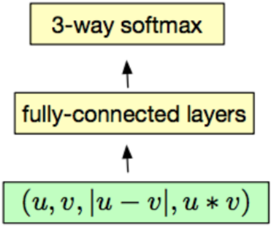
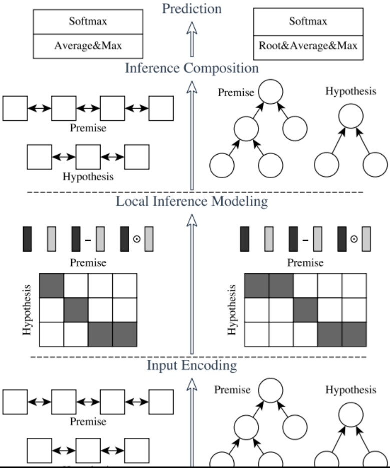
BiLSMT composition





ESIM


Prediction
Softmax
Average&Max
Softmax
Root&Average&Max
Inference Composition
Premise
Hypothesis
Premise
Hypothesis
Local Inference Modeling
Premise
Hypothesis
Premise
Hypothesis
Input Encoding
Premise
Hypothesis
Premise

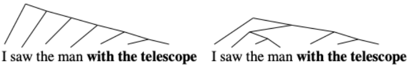
ESIM

$$
\begin{aligned}
\mathbf{t}_i &= \text{emb}(t_i; \omega_{\text{emb}}) && \text{(1a)}\\
\mathbf{h}_j &= \text{emb}(h_j; \omega_{\text{emb}}) && \text{(1b)}\\
\mathbf{s}_1^m &= \text{birnn}(\mathbf{t}_1^m; \omega_{\text{enc}}) && \text{(1c)}\\
\mathbf{u}_1^n &= \text{birnn}(\mathbf{h}_1^n; \omega_{\text{enc}}) && \text{(1d)}\\
\mathbf{a}_i &= \text{attention}(\mathbf{s}_i, \mathbf{u}_1^n) && \text{(1e)}\\
\mathbf{b}_j &= \text{attention}(\mathbf{u}_j, \mathbf{s}_1^m) && \text{(1f)}\\
\mathbf{c}_i &= [\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}_i - \mathbf{a}_i, \mathbf{s}_i \odot \mathbf{a}_i] && \text{(1g)}\\
\mathbf{d}_j &= [\mathbf{u}_j, \mathbf{b}_j, \mathbf{u}_j - \mathbf{b}_j, \mathbf{u}_j \odot \mathbf{b}_j] && \text{(1h)}\\
\mathbf{c}_1^m &= \text{birnn}(\mathbf{c}_1^m; \omega_{\text{comp}}) && \text{(1i)}\\
\mathbf{d}_1^n &= \text{birnn}(\mathbf{d}_1^n; \omega_{\text{comp}}) && \text{(1j)}\\
\mathbf{q} &= [\text{avg}(\mathbf{c}_1^m), \text{maxpool}(\mathbf{c}_1^m), \text{avg}(\mathbf{d}_1^n), \text{maxpool}(\mathbf{d}_1^n)] && \text{(1k)}\\
\mathbf{q} &= \tanh(\text{affine}(\mathbf{q}; \omega_{\text{hid}})) && \text{(1l)}\\
f(x) &= \text{softmax}(\text{mlp}(\mathbf{q}; \omega_{\text{cls}})) && \text{(1m)}
\end{aligned}
$$

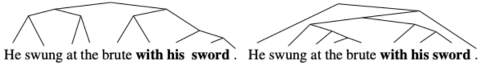
Outline

1. Introduction
   - Applications of Textual Entailment
2. Levels of Representation
3. RTE Methods
   - Evaluation
4. Current Methods
5. Latent Variable Models
6. Uncertainty in Natural Language Inference

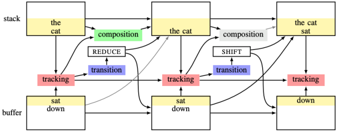
Latent Structure Induction

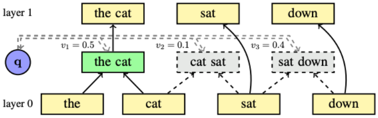


(a) Two parse trees correspond to two distinct interpretations for the sentence in example (1).



(b) Parses generated by at ST-Gumbel model (left) and the Stanford Parser (right).





Deep Generative Models

- Model that generates **hypothesis** and **decision** given a text and a stochastic embedding of the hypothesis-decision pair.

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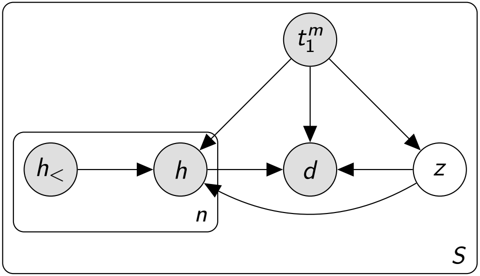
- Model that generates **hypothesis** and **decision** given a text and a stochastic embedding of the hypothesis-decision pair.
- Models to learn from mixed-domain NLI data e.g. by capitalising on lexical domain-dependent patterns.
- Performance of standard classifiers tend to vary across domains and especially out of domain.

Deep Generative Models



$$Z_i | t_1^m \sim \mathcal{N}(\mu(s_1^m), \sigma^2(s_1^m))$$
$$H_i | z_1^m \sim Cat(f(z_1^m, t_1^m; \theta))$$
$$D_j | z_1^m, h_1^n \sim Cat(g(z_1^m, t_1^m, h_1^n; \theta))$$

Deep Generative Models I

- Joint likelihood of y (hypothesis) and d (decision)

$$p(y, d|x, \theta) = \int p(z|x, \theta) p(y|x, z, \theta) p(d|x, y, z, \theta) dz. \quad (2)$$

- The *hypothesis generation model*:

$$p(y|x, z, \theta) = \prod_{j=1}^{|y|} p(y_j|x, z, y_{<j}, \theta) = \prod_{j=1}^{|y|} \mathrm{Cat}(y_j | f_o(x, z, y_{<j}; \theta)) \;, \quad (3)$$

Deep Generative Models II

- The *classification model* ESIM:

$$p(d|x, y, z, \theta) = \mathrm{Cat}(d|f_c(x, y, z; \theta)) \tag{4}$$

- Lowerbound on the log-likelihood function (ELBO)

$$\begin{aligned} \mathcal{L}(\theta, \phi) = \mathbb{E}_{q(z|x,y,d,\phi)} [\log p(y, d|x, z, \theta)] \\ - \mathrm{KL}(q(z|x, y, d, \phi)||p(z|x, \theta)) \end{aligned} \tag{5}$$

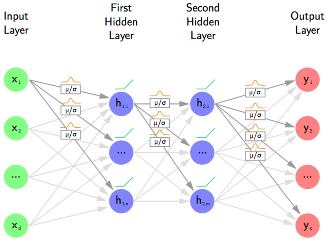
Deep Generative Models

Model	Dev	
	matched	mismatched
$\text{ESIM}_{\text{mnli}}$	74.39 ± 0.11	74.05 ± 0.21
$+\ \mathcal{N}\text{-VAE}_{50z}$	74.89 ± 0.25	74.07 ± 0.37
$+\ \mathcal{N}\text{-VAE}_{100z}$	74.82 ± 0.28	73.91 ± 0.59
$+\ \mathcal{N}\text{-VAE}_{256z}$	74.87 ± 0.15	74.08 ± 0.16

Outline

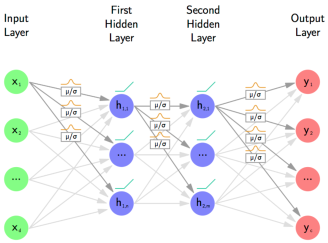
Bayes by backprop

- NNs perform well with lots of data, however they fail to express uncertainty with little or no data,
leading to overconfident decisions.



Bayes by backprop

- NNs perform well with lots of data, however they fail to express uncertainty with little or no data,
leading to overconfident decisions.
- Bayesian neural networks introduce probability distributions over the weights.



Bayes by backprop

- However, Bayesian inference on the parameters ω of a neural network is intractable, with data D.

$$p(\omega|\mathcal{D}) = \frac{p(\mathcal{D}|\omega)p(\omega)}{p(\mathcal{D})} = \frac{p(\mathcal{D}|\omega)p(\omega)}{\int p(\mathcal{D}|\omega)p(\omega)\mathrm{d}\omega} \tag{6}$$

(Blundell et al., 2015)

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- We need an approximation $q(\omega|\theta)$, over the weights that approximates the true posterior
- The ELBO is:

$$\begin{aligned} \mathcal{L}(\mathcal{D},\theta) &= \int q(\omega|\theta)\log\frac{q(\omega|\theta)}{p(\omega)} - q(\omega|\theta)\log p(\mathcal{D}|\omega)\mathrm{d}\omega \\ &= \mathrm{KL}[q(\omega|\theta)||p(\omega)] - \mathbb{E}_{q(\omega|\theta)}[\log p(\mathcal{D}|\omega)] \end{aligned} \tag{7}$$

(Blundell et al., 2015)

MC dropout I

- On NLI training inputs $X = \langle (t_1, h_1), \ldots, (t_n, h_n) \rangle$ are premise (t) and hypothesis (h) pairs, and the corresponding outputs $Y = \langle y_1, \ldots, y_n \rangle$ over N instances.
- The likelihood for classification is defined by:

$$p(y|x, \omega) = \text{Cat}(y|f(x; \omega)), \tag{8}$$

over y entailment relations computed by mapping from the input to the class probabilities with a neural network f parameterised by ω.

MC dropout II

- A Bayesian NN (MacKay, 1992) is defined by placing a prior distribution over the model parameters $p(\omega)$, where this prior is often a Gaussian distribution $p(\omega) \sim \mathcal{N}(0, I)$.
- The Bayesian NN formulation leads to a posterior distribution over the parameters given our observed data, instead of a single estimate.
- We are interested on estimating the posterior distribution over the parameters $p(\omega|\mathcal{D})$, given our observed data X, Y.
- The goal is to predict a new input instances by marginalising over the parameters:

$$p(y^*|x^*, \mathcal{D}) = \int p(y^*|x^*, \omega)p(\omega|\mathcal{D})d\omega. \tag{9}$$

MC dropout III

- However, the true posterior $p(\omega|\mathcal{D})$ is intractable, and Gal and Ghahramani (2016a) use variational inference to approximate this posterior.
- We define an approximate distribution $q_\theta(\omega)$, to minimise the KL divergence between the approximation and the true posterior.
- The objective for optimisation is a lower-bound on the log-likelihood function (ELBO):

$$\mathcal{L} = \mathbb{E}_{q(\omega)}\left[\sum_{i=1}^{N} \log p(y_i|f(x_i;\omega))\right] - \mathrm{KL}(q_\theta(\omega))||p(\omega)), \tag{10}$$

MC dropout IV

where the KL term is approximated with L_2 regularisation.

- Gal and Ghahramani (2016a) show that the use of dropout in NNs before each weight layer is an approximation to variational inference in Bayesian NNs.
- By replacing the true posterior $p(\omega|\mathcal{D})$ with the approximate posterior $q_\theta(\omega)$, we obtain a Monte Carlo (MC) estimate for future predictions :

$$\begin{aligned} p(y^*|x^*, \mathcal{D}) &\approx \int p(y^*|x^*, \omega) q_\theta(\omega) d\omega \\ &\approx \frac{1}{T} \sum_t^T p(y^*|x^*, \hat{\omega}_t), \end{aligned} \tag{11}$$

MC dropout V

where $\hat{\omega}_t \sim q_\theta(\omega)$

- In practice, the approximation to the predictive distribution is based on performing T stochastic forward passes through the network and averaging the results.
- In other words, this is achieved by performing **dropout at test time** (MC dropout).
- Finally, for classification, a way to quantify uncertainty is by computing the entropy of the output probability vector $\mathcal{H}(p) = -\sum_{c=1}^{C} p_c \log p_c$ over c classes.

Uncertainty in natural language inference

- ESIM for classification (without syntactic parses)

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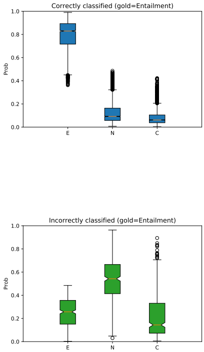
- Finally, for the additional L_2 regularisation, we use a separate weight decay: for weights $\lambda_\omega = \frac{1-p_{\text{drop}}}{N}$ with p_{drop} dropout, and for biases (b): $\lambda_b = \frac{1}{N}$.

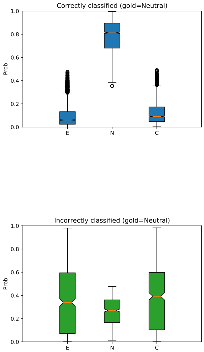
Results

Training	Model	SNLI	Breaking NLI
SNLI	ESIM†	87.9	65.6
	ESIM$_{\text{ours}}$	86.4 ± 0.09	57.6 ± 1.9
	ESIM$_{\text{MC}}$	86.5 ± 0.13	68.9 ± 1.7
MNLI+SNLI	ESIM†	86.3	74.9
	ESIM$_{\text{ours}}$	86.8 ± 0.05	68.8 ± 3.5
	ESIM$_{\text{MC}}$	86.6 ± 0.16	75.2 ± 1.3

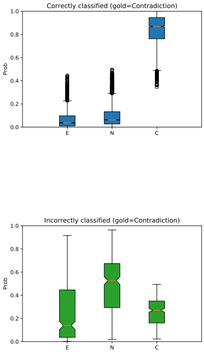
Results SNLI



(d) Gold label entailment.

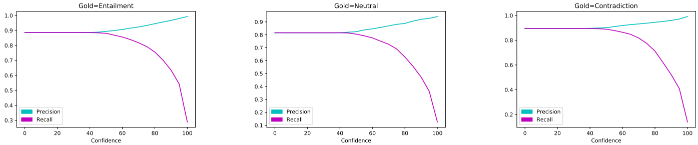


(e) Gold label neutral.

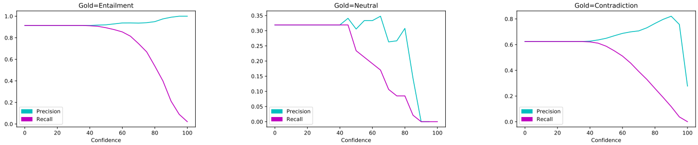


(f) Gold label contradiction.

Results SNLI and Breaking



(g) SNLI



(j) Breaking

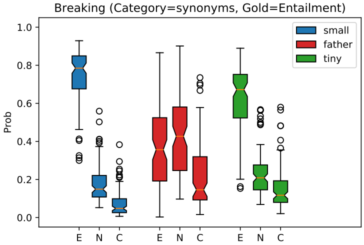
Results

P: The little girl is riding in the car with her dad.
H: The small girl is riding in the car with her dad.

P: The little girl is riding in the car with her dad.
H: The little girl is riding in the car with her father.

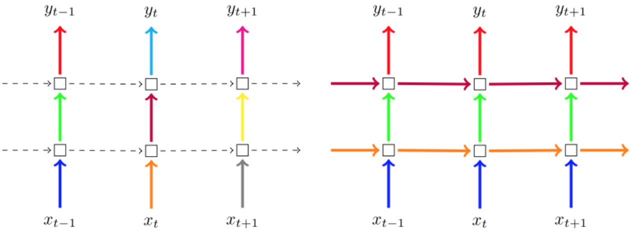
P: The little girl is riding in the car with her dad.

H: The tiny girl is riding in the car with her dad.



Homework!!

- Dropout in Recurrent Networks (Gal and Ghahramani, 2016b)
- Use the same dropout mask at each time step for both inputs, outputs, and recurrent layers
- The RNN can be framed as a probabilistic model.



(a) Naive dropout RNN (b) Variational RNN

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Max Glockner, Vered Shwartz, and Yoav Goldberg. Breaking NLI systems with sentences that require simple lexical inferences. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 650–655, Melbourne, Australia, July 2018. Association for Computational Linguistics. URL https://www.aclweb.org/anthology/P18-2103.

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