Generative models for natural language inference

DGM4NLP

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Outline

Introduction

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- We say that T entails H if the meaning of H can be inferred from the meaning of T, as would typically be interpreted by people.
  $T \rightarrow H$

> T: The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure.
> H: BMI acquired an American company.

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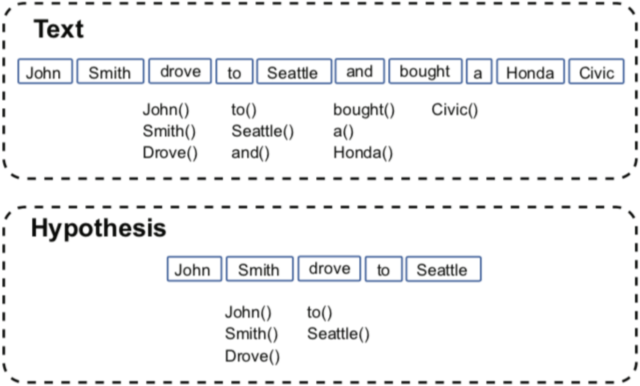
- The representation (e.g. words, syntax, semantics) of the T-H pair that is used to extract features to train a supervised classifier.

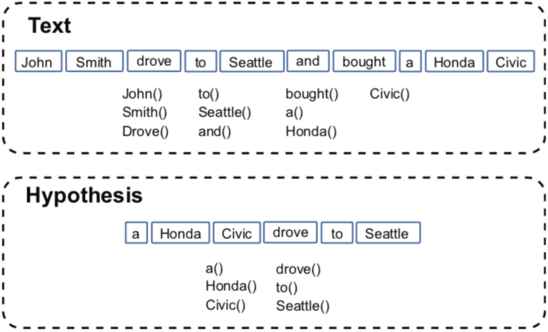
Lexical level

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



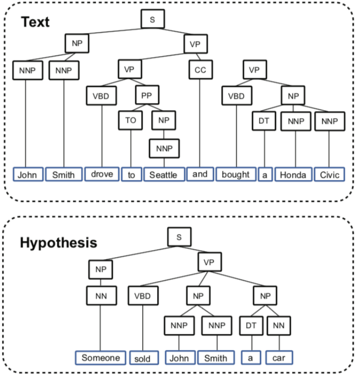
Lexical level

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



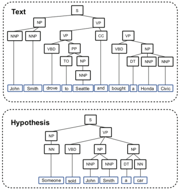
Structural level

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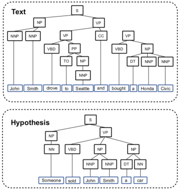
- “John” and “drove,” but the two words are **separated** by a sequence of dependency edges.



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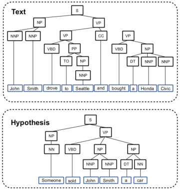
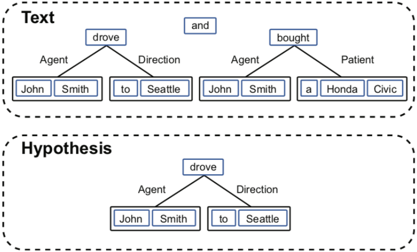
- Given the expressiveness of the dependency representation, many possible sequences of edges that could represent connection, and many other sequences that do not.



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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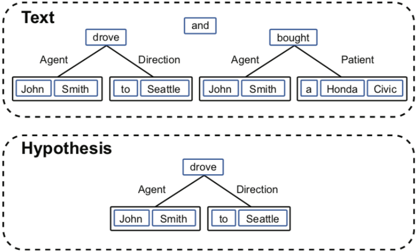

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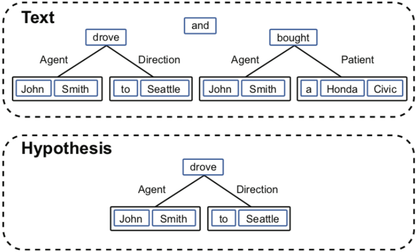
- "John" is an argument of the predicate "drove"



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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  The attack frame, and specifies events: 'assailant', a 'victim', a 'weapon', etc.
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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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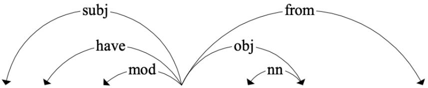

They had previously bought bighorn sheep from Comstock.

(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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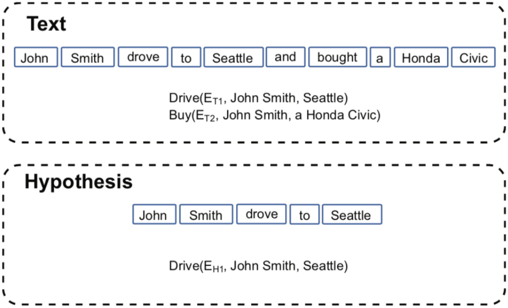

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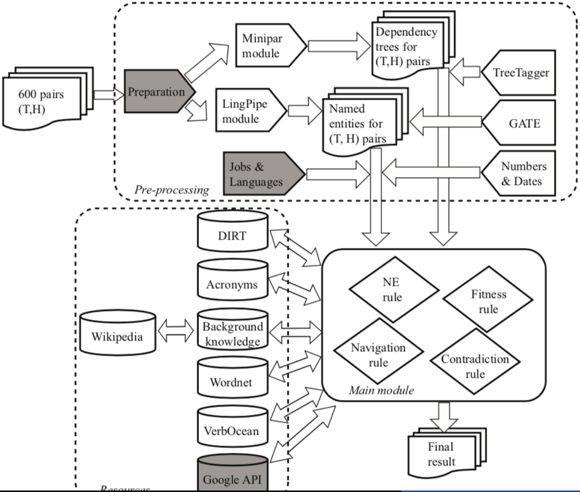
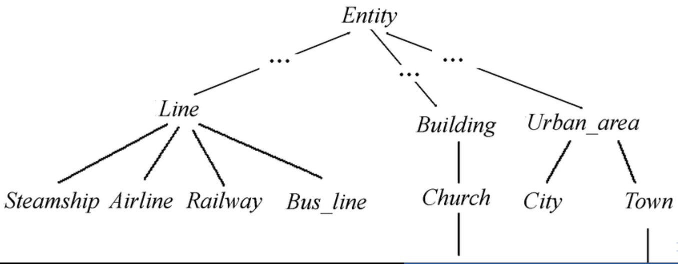


Similarity-based approaches

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



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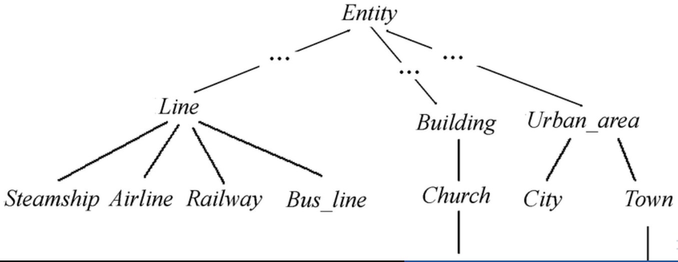

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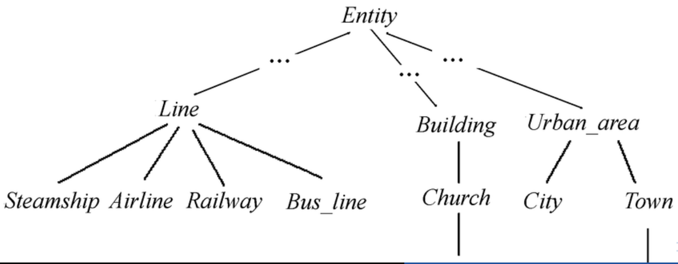

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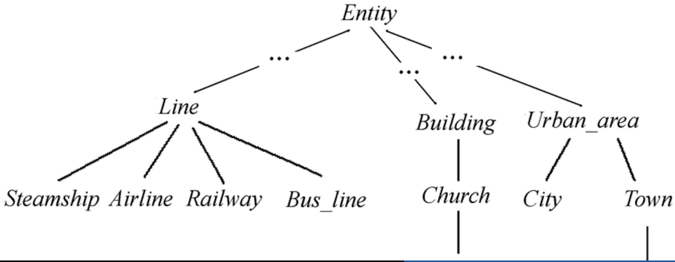
- Similarity scores computed from different linguistic levels. The goal is to find complementary features.



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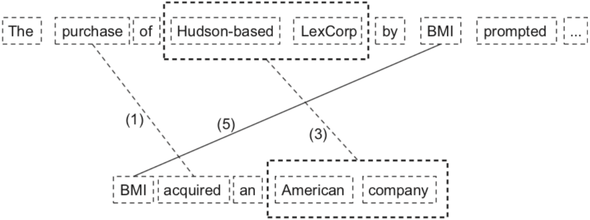

- (1,purchase,acquired)
  (3,Hudson-based LexCorp, American company),
  (5,BMI,BMI)

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

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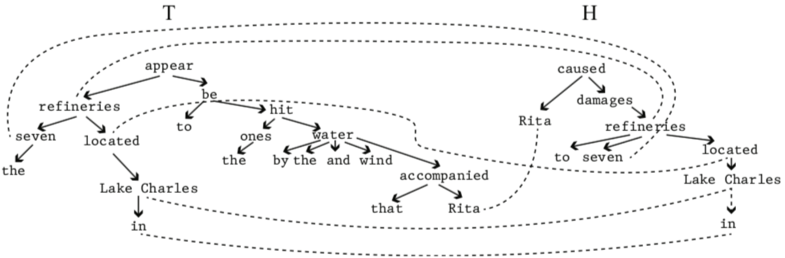

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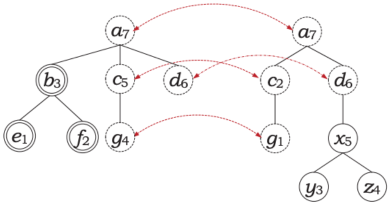
- T entails H if there is a **sequence of transformations** applied to T such that we can obtain H with an overall cost below a certain **threshold**.



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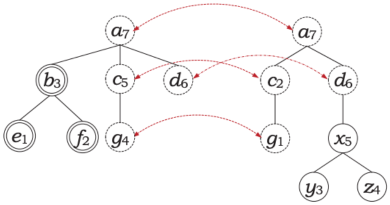

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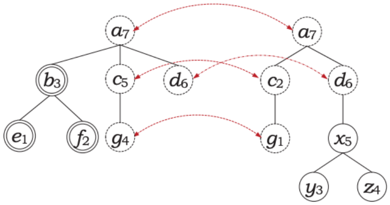

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- RTE-4 and RTE-5 increase the difficulty by adding irrelevant signals (additional words, phrases, and sentences).

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

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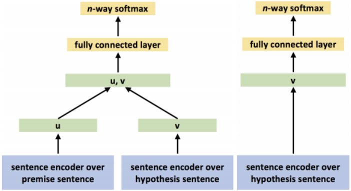
- T: 8 million in relief in the form of emergency housing.
  H: The 8 million dollars for emergency housing was still not enough to solve the problem.
  Government

Drawbacks



Premise	A woman selling bamboo sticks talking to two men on a loading dock.
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Contradiction	A woman is **not** taking money for any of her sticks.

- Entailment: animal, instrument, and outdoors.

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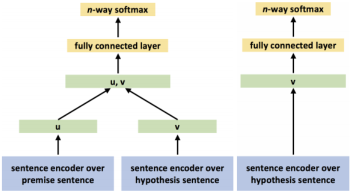

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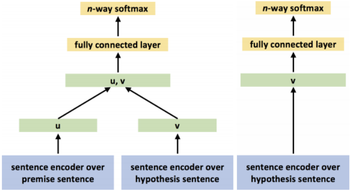

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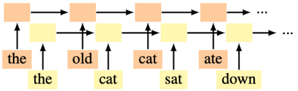
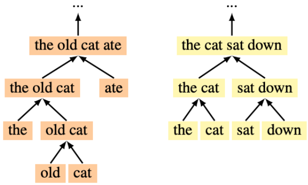
- Contradiction: Negation words, nobody, no, never and nothing

Neural Network Models

- Embeddings like glove or elmo, for fine tuning.



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



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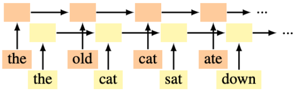

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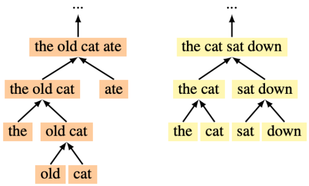

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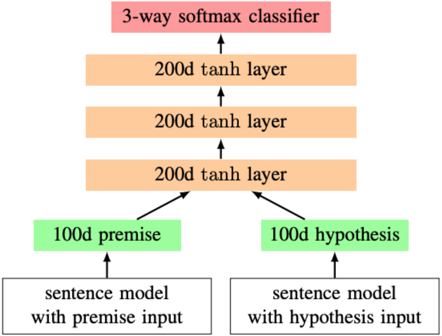
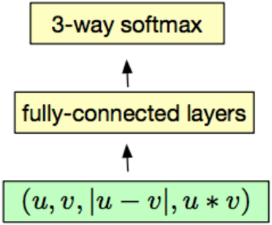
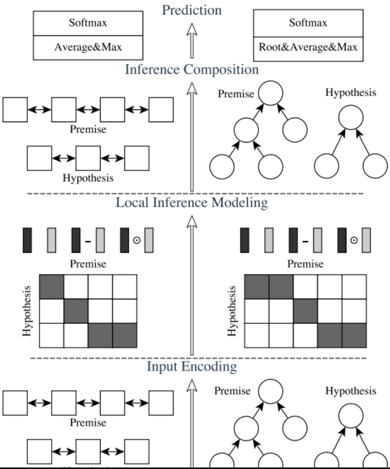
BiLSMT composition





ESIM

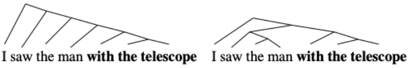

Softmax
Average&Max
Prediction
Softmax
Root&Average&Max
Inference Composition
Premise
Hypothesis
Premise
Hypothesis
Local Inference Modeling
Premise
Hypothesis
Premise
Hypothesis
Input Encoding
Premise
Hypothesis
Premise

ESIM

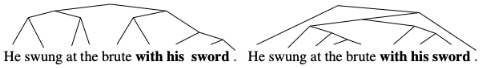
$$
\begin{aligned}
\mathbf{t}_i &= \mathrm{emb}(t_i; \omega_{\mathrm{emb}}) && \text{(1a)}\\
\mathbf{h}_j &= \mathrm{emb}(h_j; \omega_{\mathrm{emb}}) && \text{(1b)}\\
\mathbf{s}_1^m &= \mathrm{birnn}(\mathbf{t}_1^m; \omega_{\mathrm{enc}}) && \text{(1c)}\\
\mathbf{u}_1^n &= \mathrm{birnn}(\mathbf{h}_1^n;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

Outline

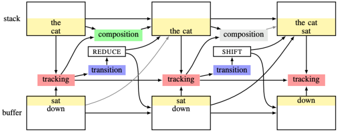
Latent Structure Induction

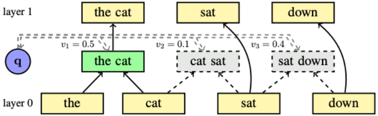


(a) Two parse trees correspond to two distinct interpretations for the sentence in example (1).



(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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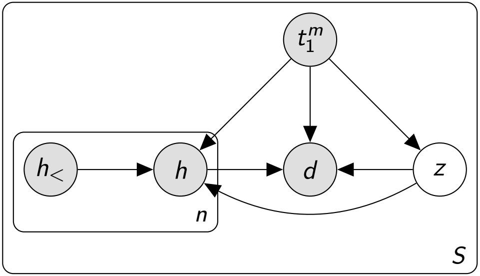
- Models to learn from mixed-domain NLI data
  e.g. by capitalising on lexical domain-dependent patterns.
- Performance of standard classifiers tend to vary across domains and especially out of domain.

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)

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

- The *hypothesis generation model*:

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

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)

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

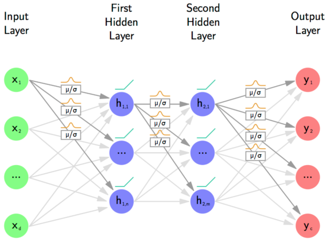
Deep Generative Models

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

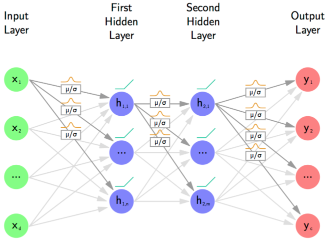
Bayes by backprop

- 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.

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

(Blundell et al., 2015)

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- 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:

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

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

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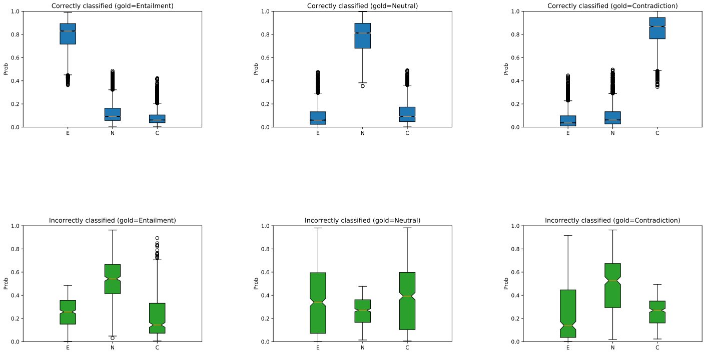
- Finally, for the additional L_2 regularisation, we use a separate weight decay: for weights $\lambda_\omega = \frac{1-p_{\text{drop}}}{N}$ with p_{drop} dropout, and for biases (b): $\lambda_{\text{b}} = \frac{1}{N}$.

Results

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

Results SNLI

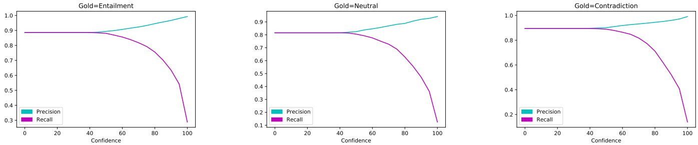


(d) Gold label entailment.

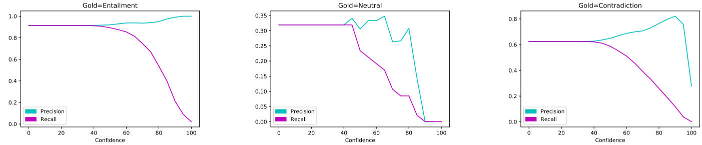
(e) Gold label neutral.

(f) Gold label contradiction.

Results SNLI and Breaking



(g) SNLI



(j) Breaking

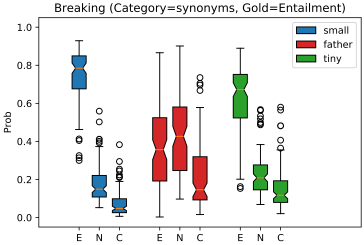
Results

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.

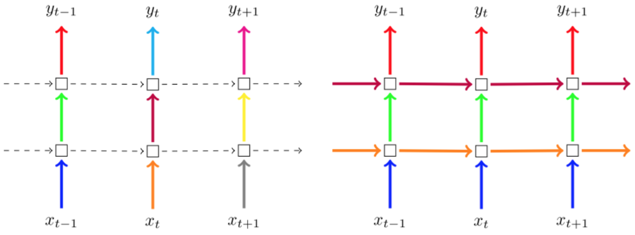
P: The little girl is riding in the car with her dad.

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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Charles Blundell, Julien Cornebise, Koray Kavukcuoglu, and Daan Wierstra. Weight uncertainty in neural networks. In *Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37*, ICML'15, pages 1613–1622. JMLR.org, 2015. URL `http://dl.acm.org/citation.cfm?id=3045118.3045290`.

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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.

David J. C. MacKay. A practical bayesian framework for backpropagation networks. *Neural Comput.*, 4(3):448–472, May 1992. ISSN 0899-7667. doi: 10.1162/neco.1992.4.3.448. URL http://dx.doi.org/10.1162/neco.1992.4.3.448.