Using Images to Ground Machine Translation

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Outline

Introduction

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- Machine Translation (MT): the task in which we wish to learn a model to translate text from one natural language (e.g., English) into another (e.g., German).
  - text-only task;
  - model is trained on parallel source/target sentence pairs.
- Image description generation (IDG): the task in which we wish to learn a model to describe an image using natural language (e.g., German).
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- Multi-Modal Machine Translation (MMT): learn a model to translate text and an image that illustrates this text from one natural language (e.g., English) into another (e.g., German).
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Use Cases

- Multi-Modal Machine Translation (MMT) use-cases:
  - localisation of product information in e-commerce, e.g. eBay, Amazon;
  - localisation of user posts and photos in social networks, e.g. Facebook, Instagram, Twitter;
  - translation of image descriptions in general;
  - translation of subtitles (video), etc.

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Convolutional Neural Networks (CNN)

- Virtually all MMT and IDG models use pre-trained CNNs for image feature extraction;
- Illustration of the VGG19 network (Simonyan and Zisserman, 2014):

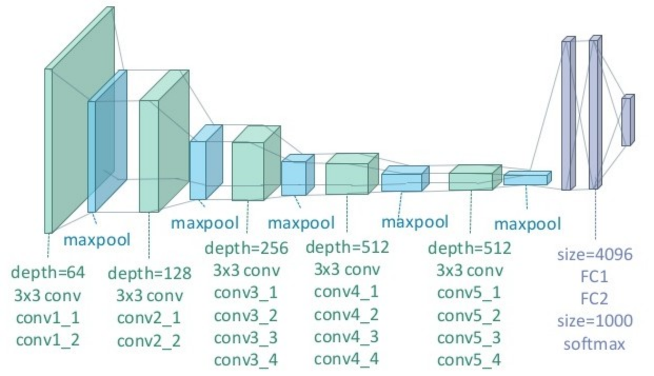
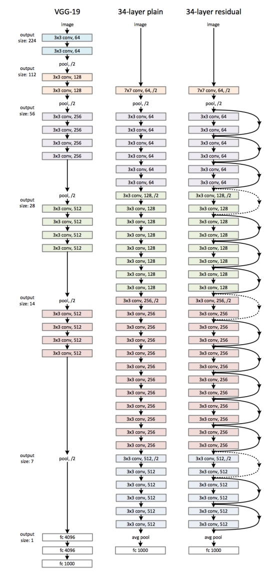
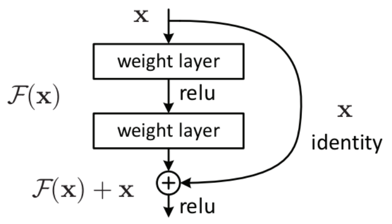


Figure 1: `https://goo.gl/y0So1l`





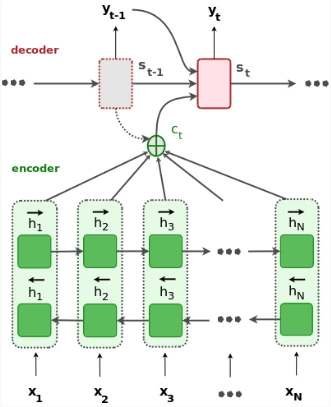
(b) Illustration of a residual connection (He et al., 2015).

(a) `https://goo.gl/jqQEvg`

NMT and IDG Architectures

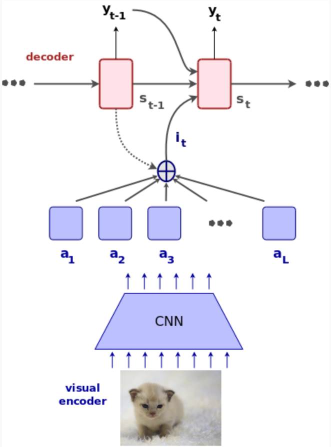
Neural Machine Translation

The attention mechanism lets the decoder search for the best source words to generate each target word, e.g. Bahdanau et al., 2015.



Neural Image Description Generation

The attention mechanism lets the decoder look at or attend to specific parts of the image when generating each target word, e.g. Xu et al., 2015.



Multi-modal MT Shared Task(s)

Multimodal MT Shared Tasks – overall ideas

- 3 types of submissions:
  - Two attention mechanisms: compute context vectors over the source language hidden states and location-preserving image features;
  - Encoder and/or decoder initialisation: initialise encoder and/or decoder RNNs with bottleneck image features;
  - Other alternatives:
    - element-wise multiplication of the target-language embeddings with bottleneck image features;
    - sum source-language word embeddings with bottleneck image features;
    - use visual features in a retrieval framework;
    - visually-ground encoder representations by learning to predict bottleneck image features from the source-language hidden states.

http://mtm2017.unbabel.com/assets/images/slides/lucia_specia.pdf

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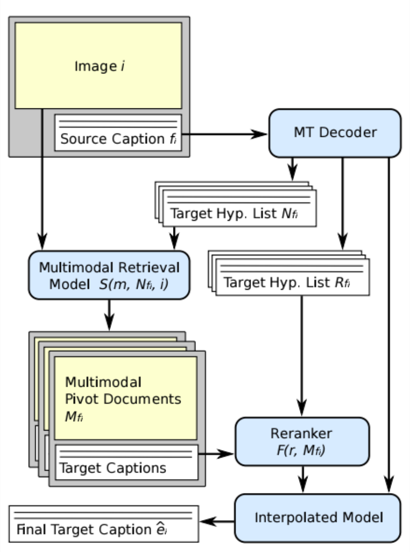
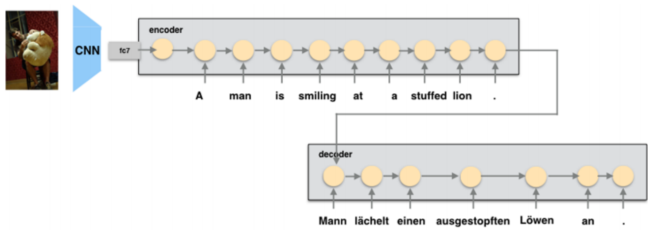
Heidelberg University (Hitschler et al., 2016)



CMU (Huang et al., 2016) [1/3]



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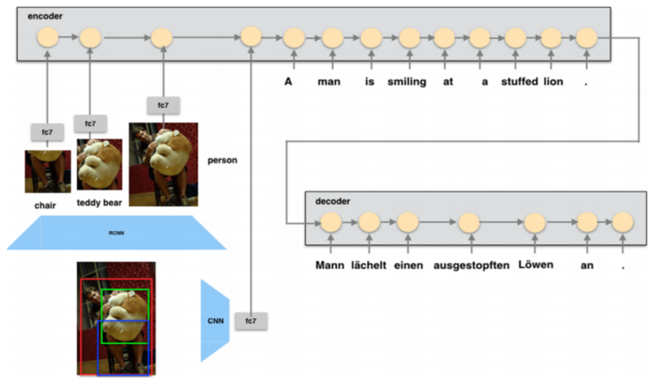

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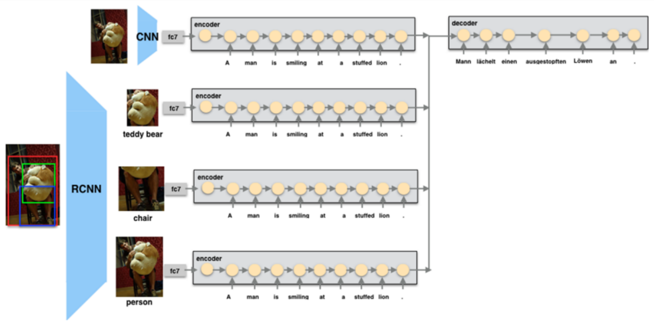
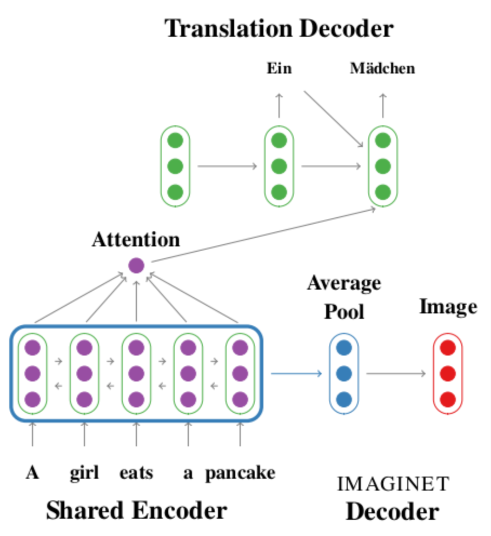


UvA-TiCC (Elliott and Kádár, 2017)



LIUM-CVC (Caglayan et al., 2017)

- Global visual features, i.e. 2048D `pool5` features from ResNet-50, are multiplicatively interacted with the target word embeddings;
- With 128D embeddings and 256D recurrent layers, their resulting models have $\sim$5M parameters.

(Elliott et al., 2017)

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Our MMT Models

Doubly-Attentive Multi-Modal NMT – $NMT_{SRC+IMG}$

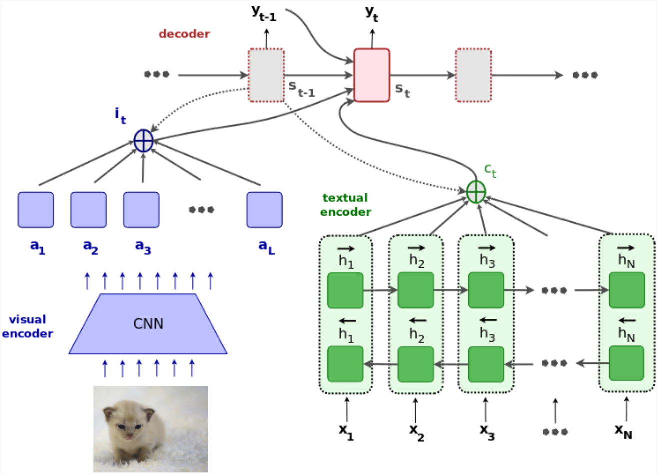


Figure 3: Doubly-Attentive Multi-modal NMT (Calixto et al., 2017a)

image gating

Image as source-language words – IMG_W

- **IMG_W** – **Global visual features** are projected into the **source-language word embeddings space** and used as the **first/last word in the source sequence**.

(Calixto et al., 2017b)

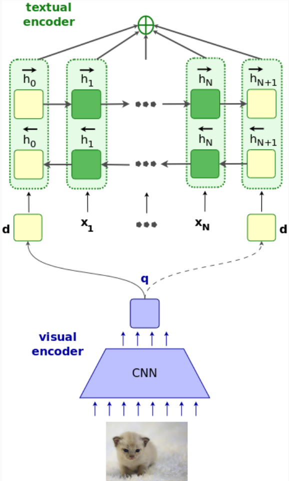
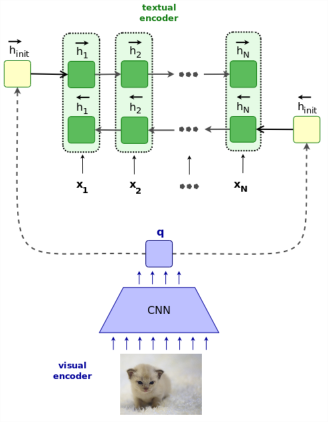


Image for encoder initialisation – IMG_E

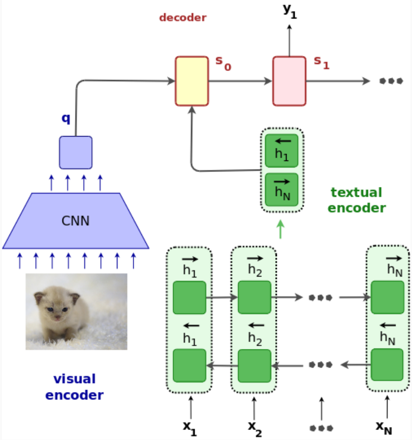
- **IMG_E** – **Global visual features** are projected into the **source-language RNN hidden states space** and used to compute the **initial state of the source-language RNN**.

(Calixto et al., 2017b)



- **IMG_D** – **Global visual features** are projected into the **target-language RNN hidden states space** and used as additional data to compute the **initial state of the target-language RNN**.

(Calixto et al., 2017b)



Experiments

- Training data: Multi30k data set (Elliott et al., 2016).

Model	**Training data**	**BLEU4**$\uparrow$	**METEOR**$\uparrow$	**TER**$\downarrow$	**chrF3**$\uparrow$
NMT	M30k$_T$	33.7	52.3	46.7	65.2
PBSMT	M30k$_T$	32.9	54.3†	45.1†	**67.4**
Huang et al., 2016	M30k$_T$	35.1 ($\uparrow$ 1.4)	52.2 ($\downarrow$ 2.1)	—	—
	+ RCNN	**36.5** ($\uparrow$ 2.8)	54.1 ($\downarrow$ 0.2)	—	—
NMT$_{SRC+IMG}$	M30k$_T$	36.5†‡ ($\uparrow$ 2.8)	55.0† ($\uparrow$ 0.9)	43.7†‡ ($\downarrow$ 1.4)	67.3 ($\downarrow$ 0.1)
IMG$_W$	M30k$_T$	36.9†‡ **($\uparrow$ 3.2)**	54.3 ‡ **($\uparrow$ 0.2)**	**41.9**†‡ **($\downarrow$ 3.2)**	66.8 ($\downarrow$ 0.6)
IMG$_E$	M30k$_T$	37.1†‡ **($\uparrow$ 3.4)**	55.0†‡ **($\uparrow$ 0.9)**	43.1†‡ **($\downarrow$ 2.0)**	67.6 ($\uparrow$ 0.2)
IMG$_D$	M30k$_T$	**37.3**†‡ **($\uparrow$ 3.6)**	**55.1**†‡ **($\uparrow$ 1.0)**	42.8†‡ **($\downarrow$ 2.3)**	**67.7** ($\uparrow$ 0.3)

English–German [2/2]

- Pre-training on back-translated comparable Multi30k data set (Elliott et al., 2016).

Model	**Training data**	**BLEU4↑**	**METEOR↑**	**TER↓**	**chrF3↑**
PBSMT (LM)	M30k$_T$	34.0	**55.0**†	44.7	**68.0**
NMT	M30k$_T$	35.5‡	53.4	43.3‡	65.2
NMT$_{SRC+IMG}$	M30k$_T$	37.1†‡ **(↑ 1.6)**	54.5† **(↓ 0.5)**	42.8†‡ **(↓ 0.5)**	66.6 **(↓ 1.4)**
IMG$_W$	M30k$_T$	36.7†‡ **(↑ 1.2)**	54.6‡ **(↓ 0.4)**	42.0†‡ **(↓ 1.3)**	66.8 **(↓ 1.2)**
IMG$_E$	M30k$_T$	**38.5**†‡ **(↑ 3.0)**	55.7†‡ **(↑ 0.9)**	**41.4**†‡ **(↓ 1.9)**	68.3 **(↑ 0.3)**
IMG$_D$	M30k$_T$	**38.5**†‡ **(↑ 3.0)**	**55.9**†‡ **(↑ 1.1)**	41.6†‡ **(↓ 1.7)**	**68.4** **(↑ 0.4)**

German–English [1/2]

- Training data: Multi30k data set (Elliott et al., 2016).

Model	**BLEU4**↑	**METEOR**↑	**TER**↓	**chrF3**↑
PBSMT	32.8	34.8	43.9	61.8
NMT	38.2	35.8	40.2	62.8
$\text{NMT}_{\text{SRC+IMG}}$	$40.6^{\dagger\ddagger}$ **(↑ 2.4)**	$37.5^{\dagger\ddagger}$ **(↑ 1.7)**	$37.7^{\dagger\ddagger}$ **(↓ 2.5)**	65.2 **(↑ 2.4)**
IMG_{W}	$39.5^{\ddagger}$ **(↑ 1.3)**	**37.1**†‡ **(↑ 1.3)**	$37.1^{\dagger\ddagger}$ **(↓ 3.1)**	63.8 **(↑ 1.0)**
IMG_{E}	$41.1^{\dagger\ddagger}$ **(↑ 2.9)**	$37.7^{\dagger\ddagger}$ **(↑ 1.9)**	$37.9^{\dagger\ddagger}$ **(↓ 2.3)**	**65.7** **(↑ 2.9)**
IMG_{D}	**41.3**†‡ **(↑ 3.1)**	**37.8**†‡ **(↑ 2.0)**	$37.9^{\dagger\ddagger}$ **(↓ 2.3)**	**65.7** **(↑ 2.9)**

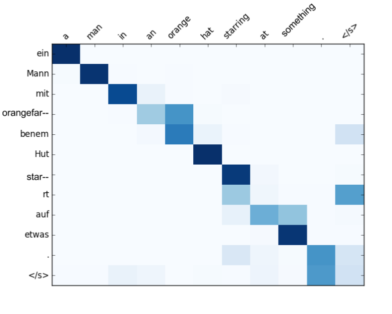
German–English [2/2]

- Pre-training on back-translated comparable Multi30k data set (Elliott et al., 2016).

Model	**BLEU4**↑	**METEOR**↑	**TER**↓	**chrF3**↑
PBSMT	36.8	36.4	40.8	64.5
NMT	42.6	38.9	36.1	67.6
$\text{NMT}_{\text{SRC+IMG}}$	43.2‡ (↑ 0.6)	39.0‡ (↑ 0.1)	35.5‡ (↓ 0.6)	67.7 (↑ 0.1)
IMG_{2W}	42.4 ‡ (↓ 0.2)	39.0 ‡ (↑ 0.1)	**34.7**†‡ **(↓ 1.4)**	67.6 (↑ 0.0)
IMG_{E}	**43.9**†‡ **(↑ 1.3)**	**39.7**†‡ **(↑ 0.8)**	34.8†‡ **(↓ 1.3)**	**68.6** **(↑ 1.0)**
IMG_{D}	43.4 ‡ (↑ 0.8)	39.3 ‡ (↑ 0.4)	35.2 ‡ (↓ 0.9)	67.8 (↑ 0.2)

NMT$_{SRC+IMG}$ — Visualisation of attention states

(a) Image–target word alignments.



(b) Source–target word alignments.

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Thank you!

Questions?