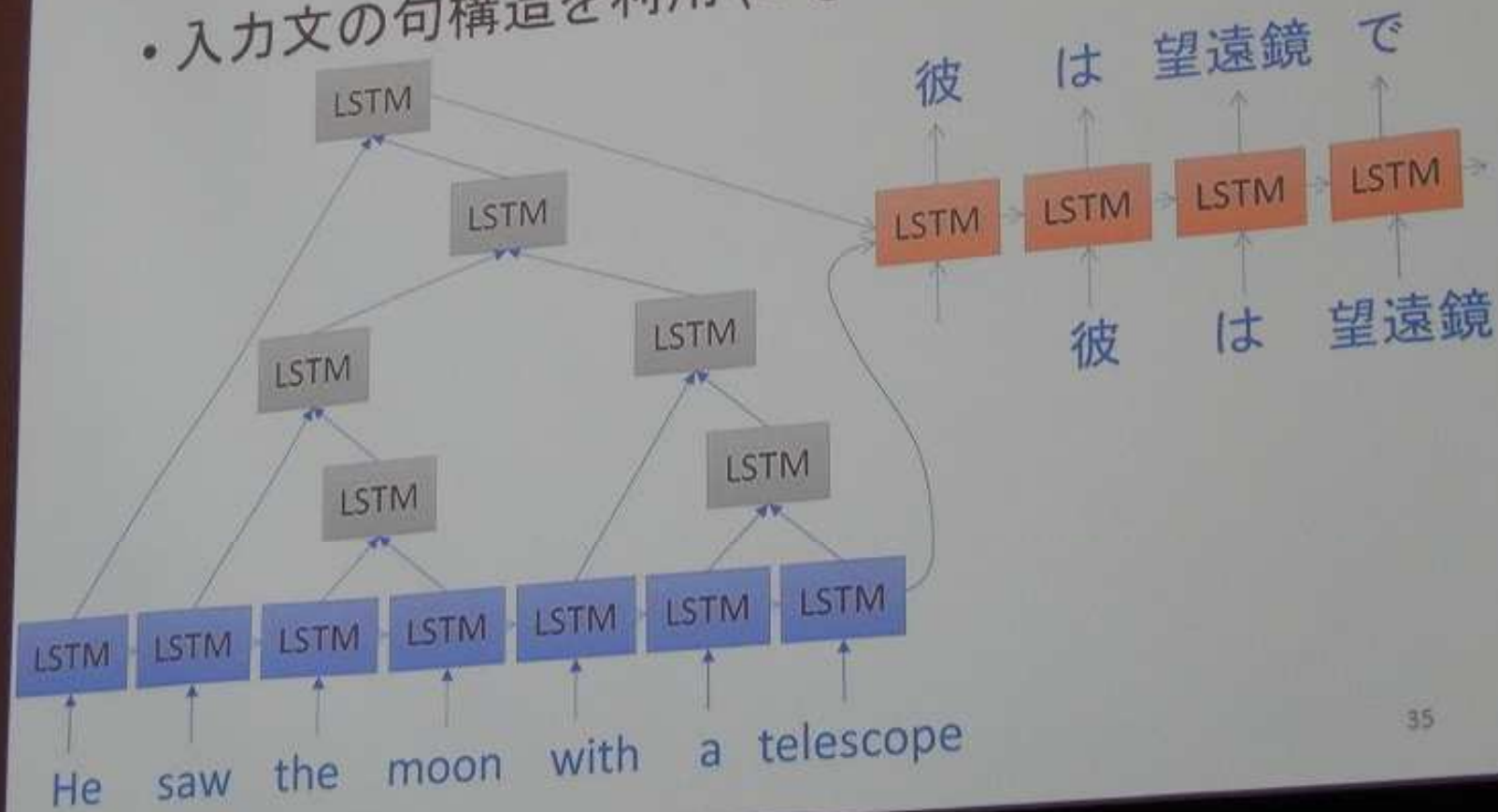


Tree-to-sequence モデル

- 入力文の句構造を利用 (Eriguchi et al. 2016)



翻訳例

In information technology and electron field, the application of nanotechnology to next generation semiconductors, high-density information record technology, miniature integrated circuit elements, electric power saving displays using carbon nano-tube, etc. can be expected.



情報技術と電子分野では、次世代半導体へのナノテクノロジーの応用、高密度情報記録技術、超小型集積回路要素、カーボンナノチューブを用いた省電力表示などが期待できる。

ニューラル会話モデル (Vinyals & Le, 2015)

- エンコーダ・デコーダモデルで会話文を学習
 - 学習データ
 - 映画の中での会話 6200万文

• 学習したモデルと人間との会話の例

Human: who is skywalker ?

Machine: he is a hero .

Human: who is bill clinton ?

Machine: he 's a billionaire .

Human: is sky blue or black ?

Machine: blue .

Human: does a cat have a tail ?

Machine: yes .

Human: does a cat have a wing ?

Machine: no

Human: can a cat fly ?

Machine: no .

Human: how many legs does a cat have ?

Machine: four , i think .

Human: how many legs does a spider have ?

Machine: three , i think .

Eメールの返事の自動生成 (Kannan et al., 2016)



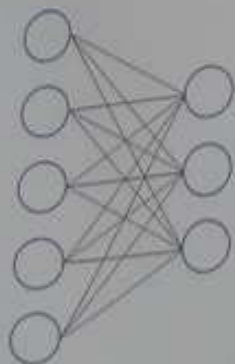
Query	Top generated responses
Hi, I thought it would be great for us to sit down and chat. I am free Tuesday and Wednesday. Can you do either of those days?	I can do Tuesday. I can do Wednesday. How about Tuesday? I can do Tuesday! I can do Tuesday. What time works for you? I can do Wednesday! I can do Tuesday or Wednesday. How about Wednesday? I can do Wednesday. What time works for you? I can do either.
Thanks!	
Alice	

Table 1: Generated response examples.

Kannan et al., Smart Reply: Automated Response Suggestion for Email, KDD 2016

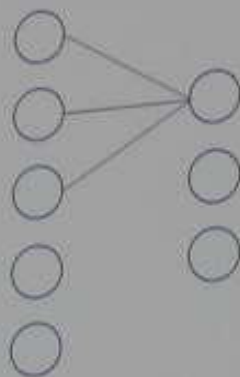
畳み込みニューラルネットワーク (Convolutional Neural Network, CNN)

- 全結合



パラメータ数
 $5 \times 3 = 15$

- 局所的結合



パラメータ数

- パラメータ共有



パラメータ数

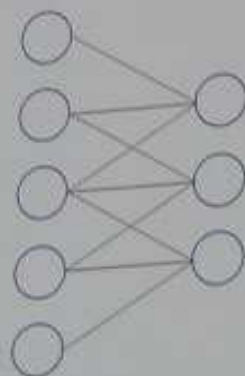
畳み込みニューラルネットワーク (Convolutional Neural Network, CNN)

- 全結合



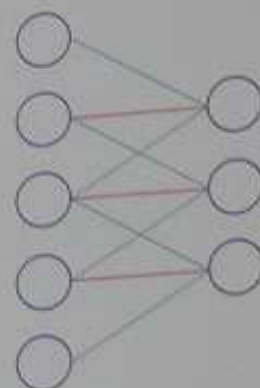
パラメータ数
 $5 \times 3 = 15$

- 局所的結合



パラメータ数
 $3 \times 3 = 9$

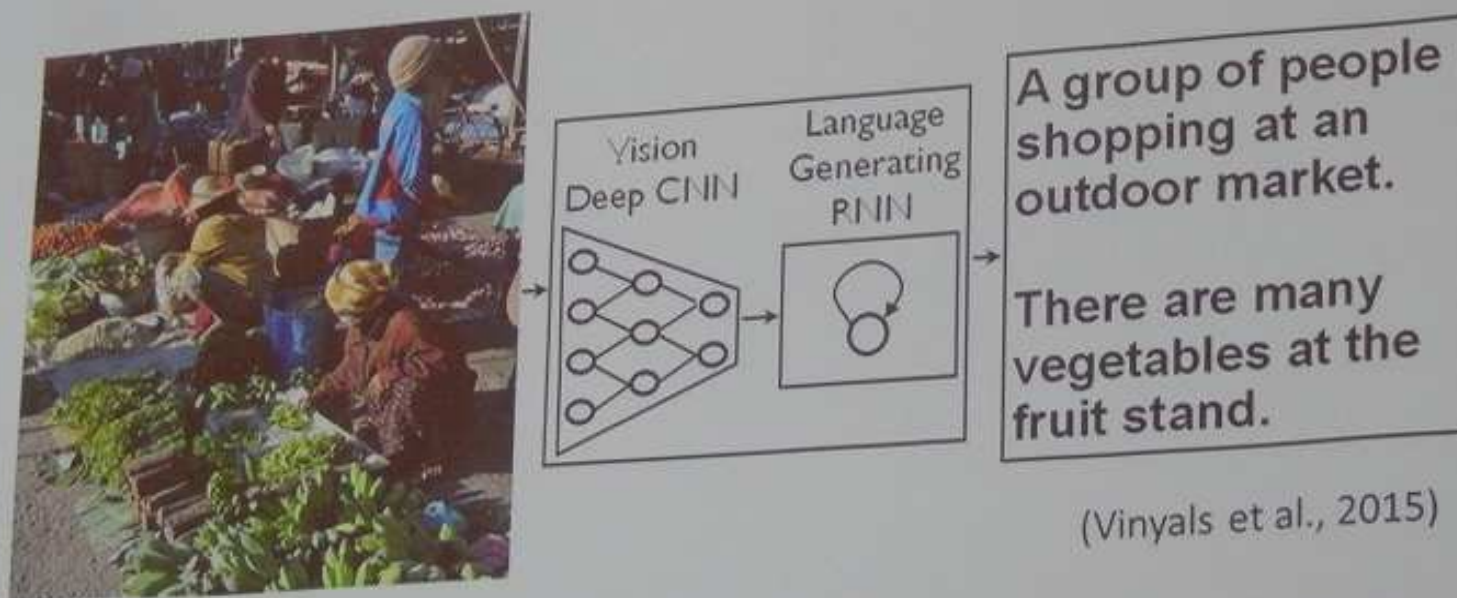
- パラメータ共有



パラメータ数
3

パラメータ数を減らすことにより過学習を回避
画像認識、テキスト分類などに有効

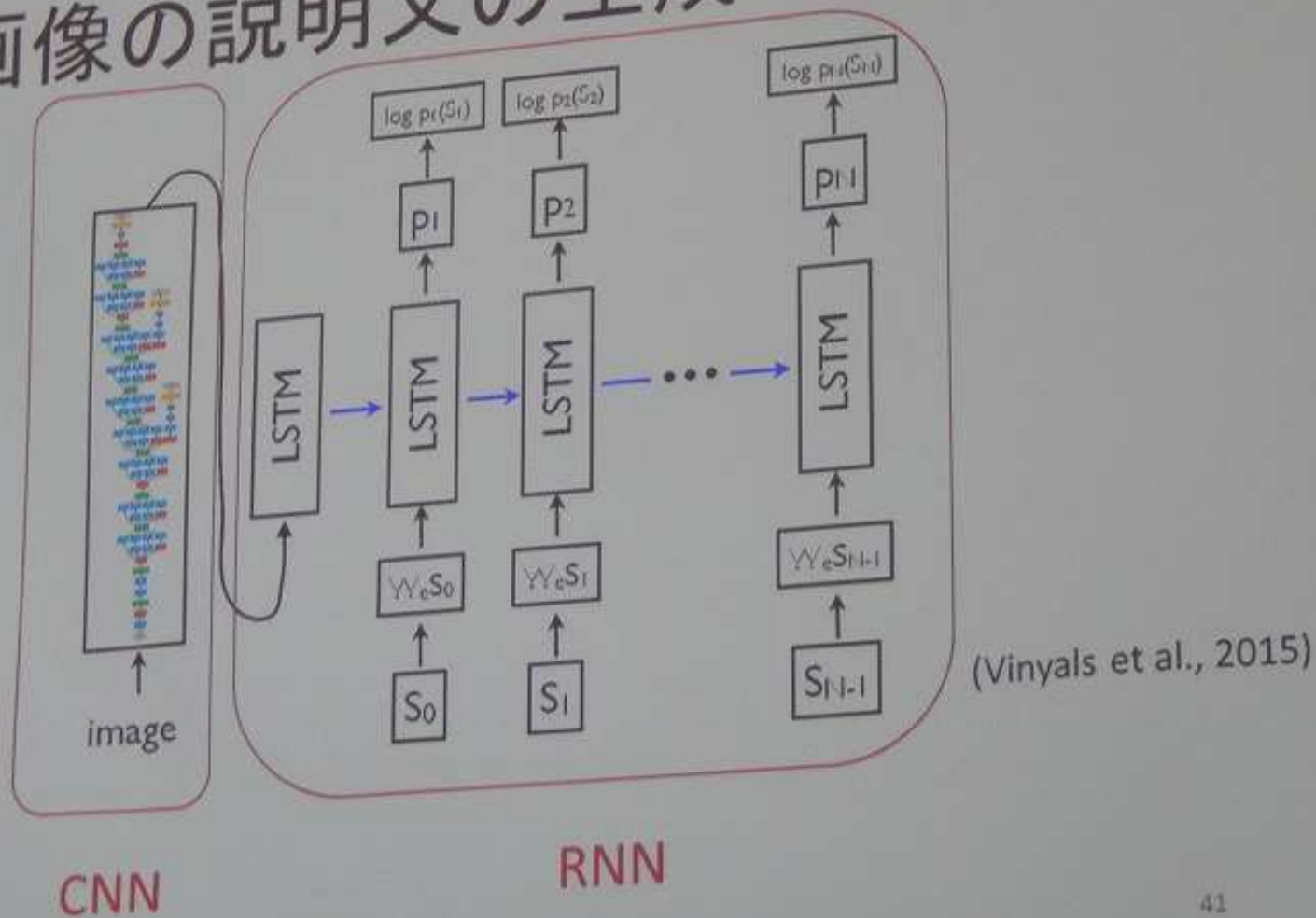
画像の説明文の生成



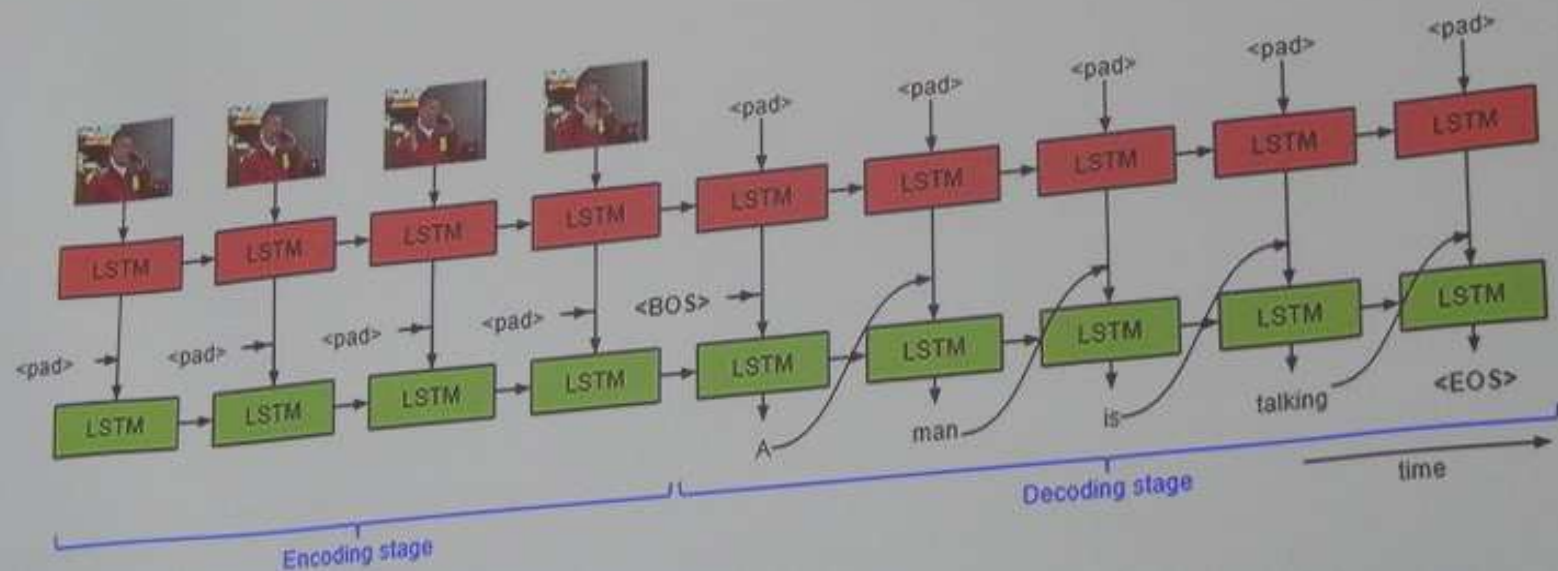
(Vinyals et al., 2015)

1. 大量のラベル付き画像で画像認識CNNを学習
2. 説明文付きの画像で言語生成RNNを学習

画像の説明文の生成



動画の説明文の生成



Venugopalan et al., Sequence to Sequence – Video to Text, ICCV 2015

動画の説明文の生成

Correct descriptions.



S2VT: A man is doing stunts on his bike.



S2VT: A herd of zebras are walking in a field.



S2VT: A young woman is doing her hair.



S2VT: A man is shooting a gun at a target.

Relevant but incorrect descriptions.



S2VT: A small bus is running into a building.



S2VT: A man is cutting a piece of a pair of a paper.



S2VT: A cat is trying to get a small board.



S2VT: A man is spreading butter on a tortilla.

Irrelevant descriptions.



S2VT: A man is pouring liquid in a pan.



S2VT: A polar bear is walking on a hill.



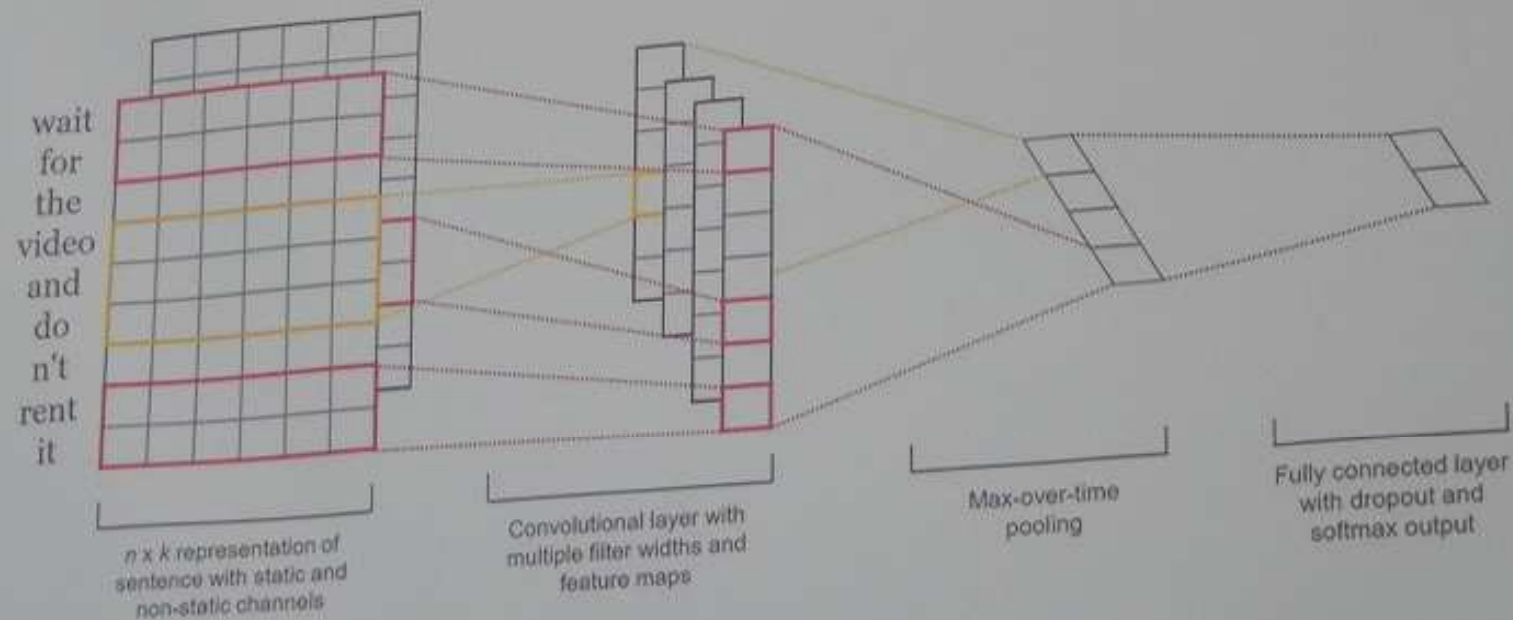
S2VT: A man is doing a pencil.



S2VT: A black clip to walking through a path.

CNN による文分類

- 単語 n-gram を(ソフトに)検出 (Kim, 2014)



SQuAD

(The Sanford Question Answering Dataset)

Rajpurkar et al. (2016)

- Wikipedia記事に関するQAデータセット
- 大規模
 - 500記事、10万QAペア
 - クラウドソーシングによって作成
- 質問の答えは文書中の単語列

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

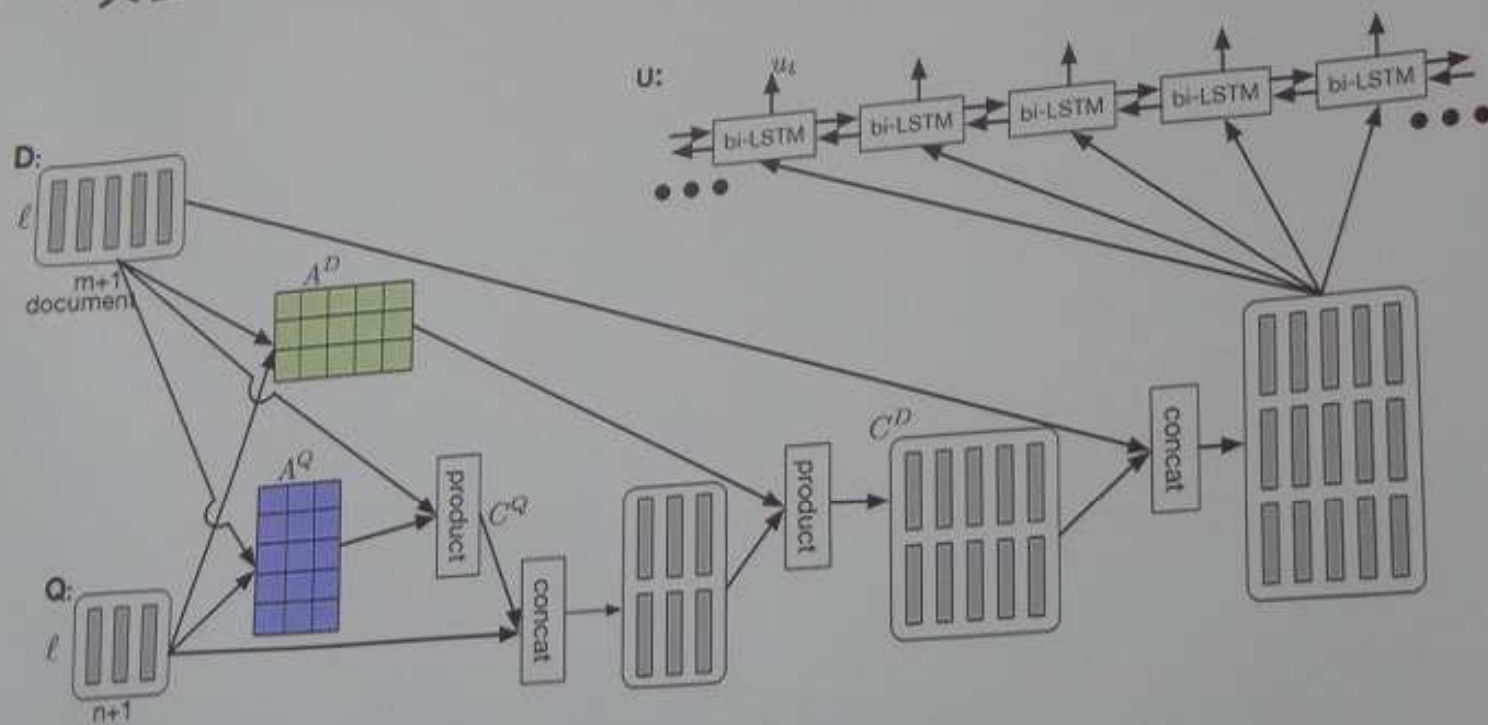
What causes precipitation to fall?
gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Dynamic Coattention Networks (Xiong et al., 2016)

- 文書と質問の中の各単語を互いの類似度で重みづけ



推論を必要とする質問応答(QA)

文書

Mary got the football there.
John moved to the bedroom.
Sandra went back to the kitchen.
Mary travelled to the hallway.
John got the football there.
John went to the hallway.
John put down the football.
Mary went to the garden.

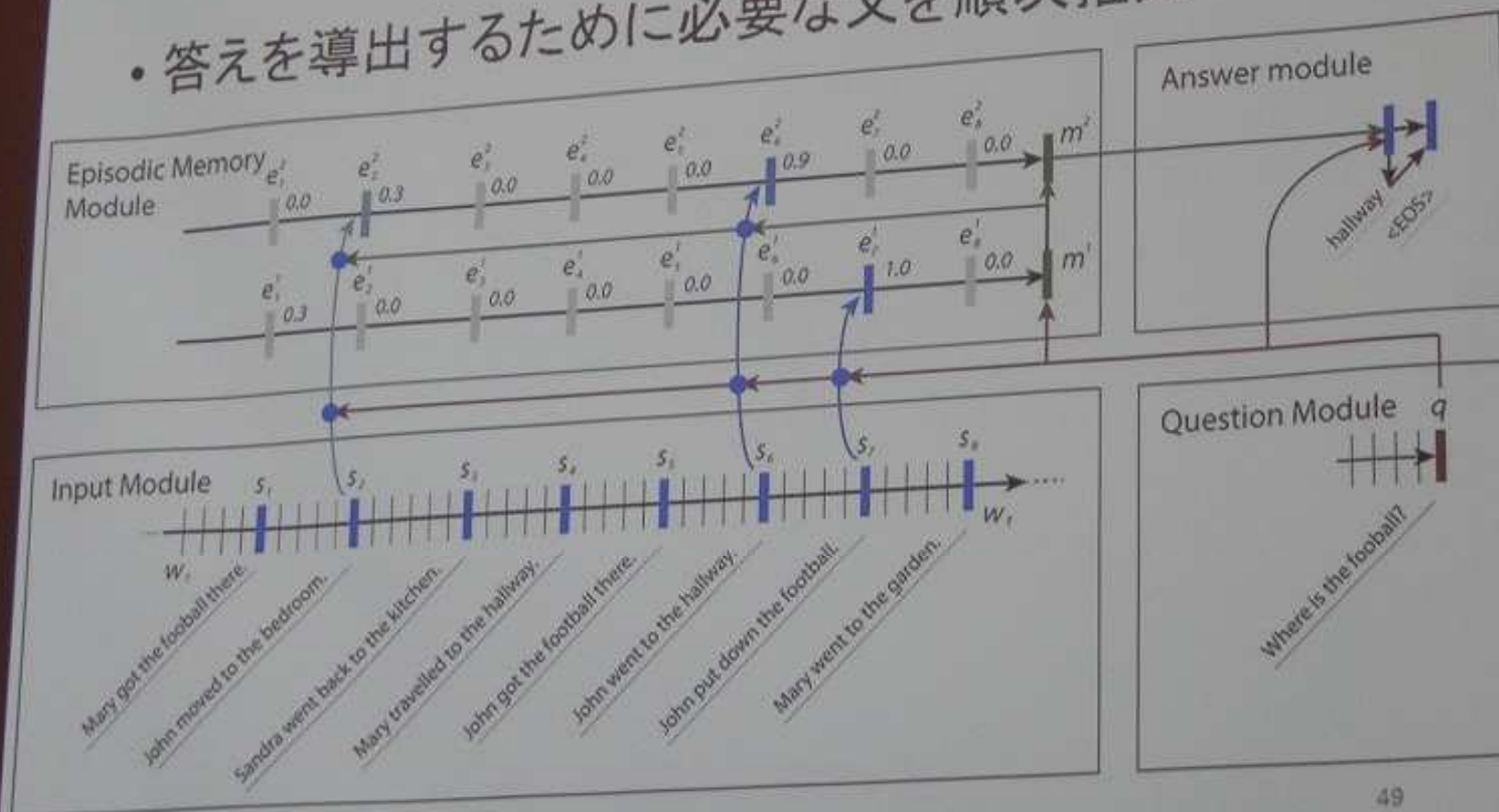
質問

Where is the football?



Dynamic Memory Networks (Kumar et al., 2016)

- 答えを導出するために必要な文を順次推定



文書要約

Original Text (truncated): lagos, nigeria (cnn) a day after winning nigeria's presidency, *muhammadu buhari* told cnn's christiane amanpour that **he plans to aggressively fight corruption that has long plagued nigeria** and go after the root of the nation's unrest. *buhari* said he'll "rapidly give attention" to curbing violence in the northeast part of nigeria, where the terrorist group boko haram operates. by cooperating with neighboring nations chad, cameroon and niger, **he said his administration is confident it will be able to thwart criminals** and others contributing to nigeria's instability. for the first time in nigeria's history, the opposition defeated the ruling party in democratic elections. *buhari* defeated incumbent goodluck jonathan by about 2 million votes, according to nigeria's independent national electoral commission. **the win comes after a long history of military rule, coups and botched attempts at democracy in africa's most populous nation.**

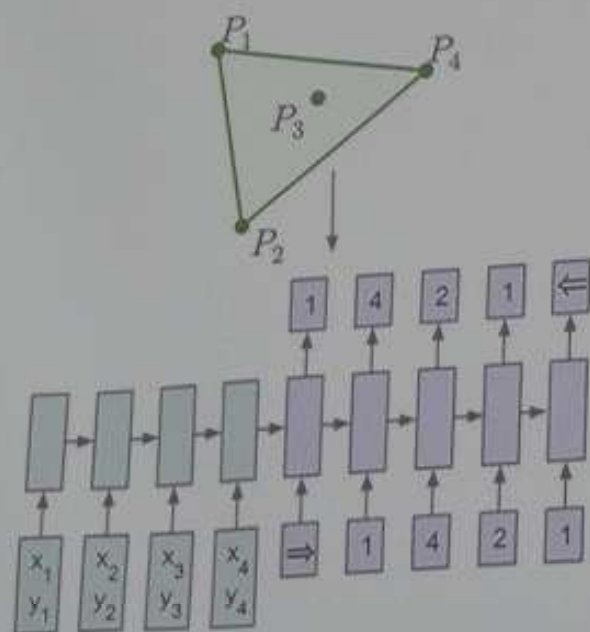
(See et al., 2017)

文書要約

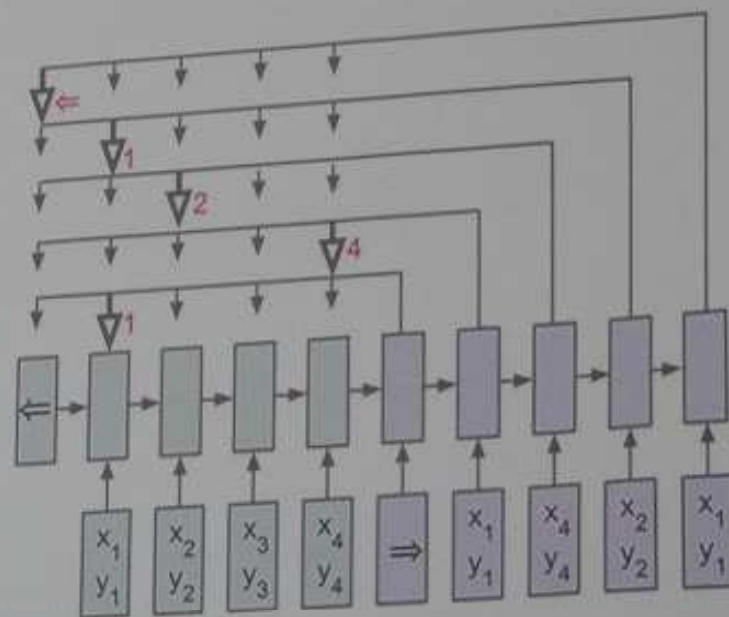
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(See et al., 2017)

Pointer networks (Vinyals et al., 2015)

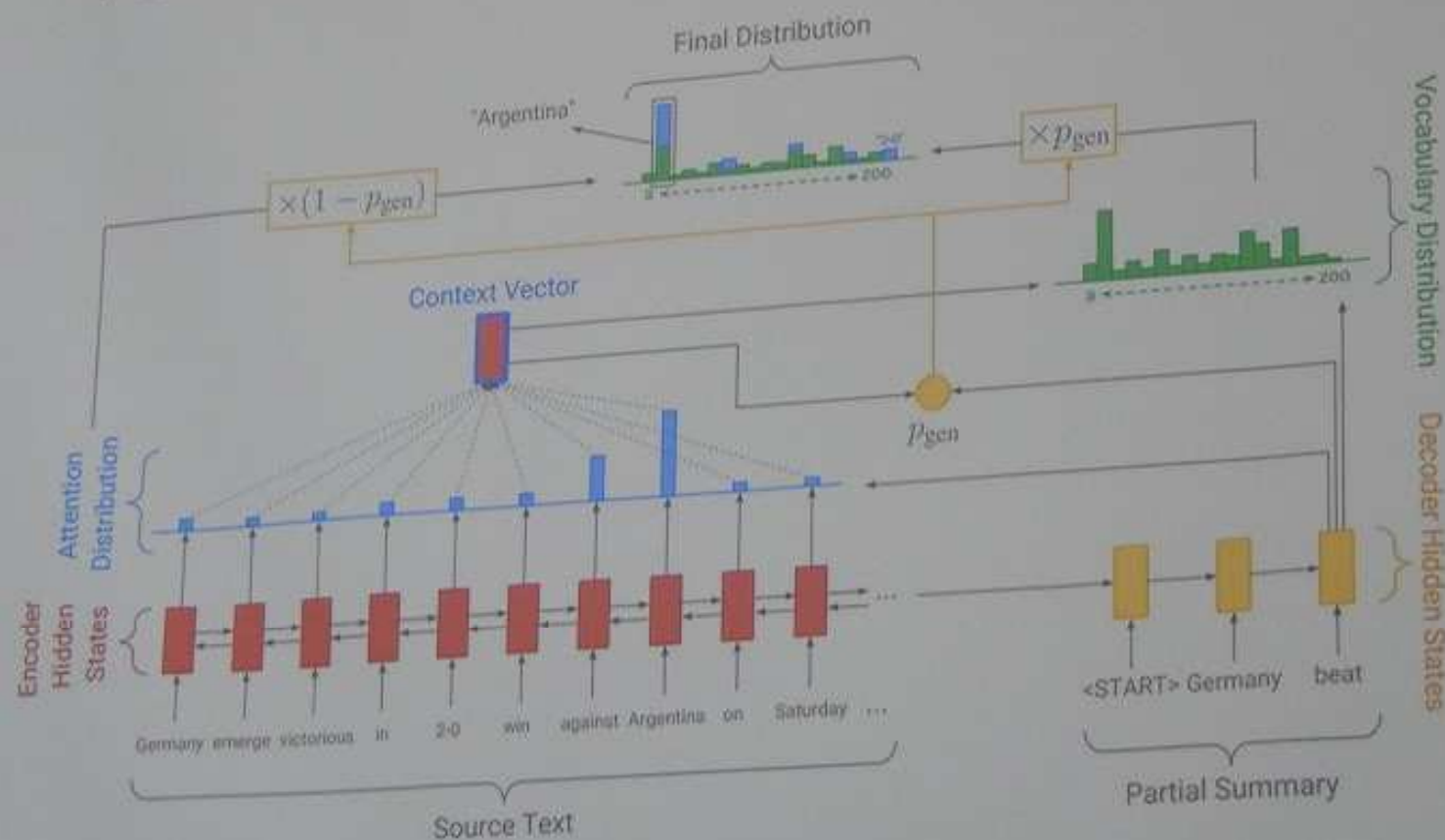


(a) Sequence-to-Sequence



(b) Ptr-Net

Pointer-generator model (See et al., 2017)



プログラム自動生成



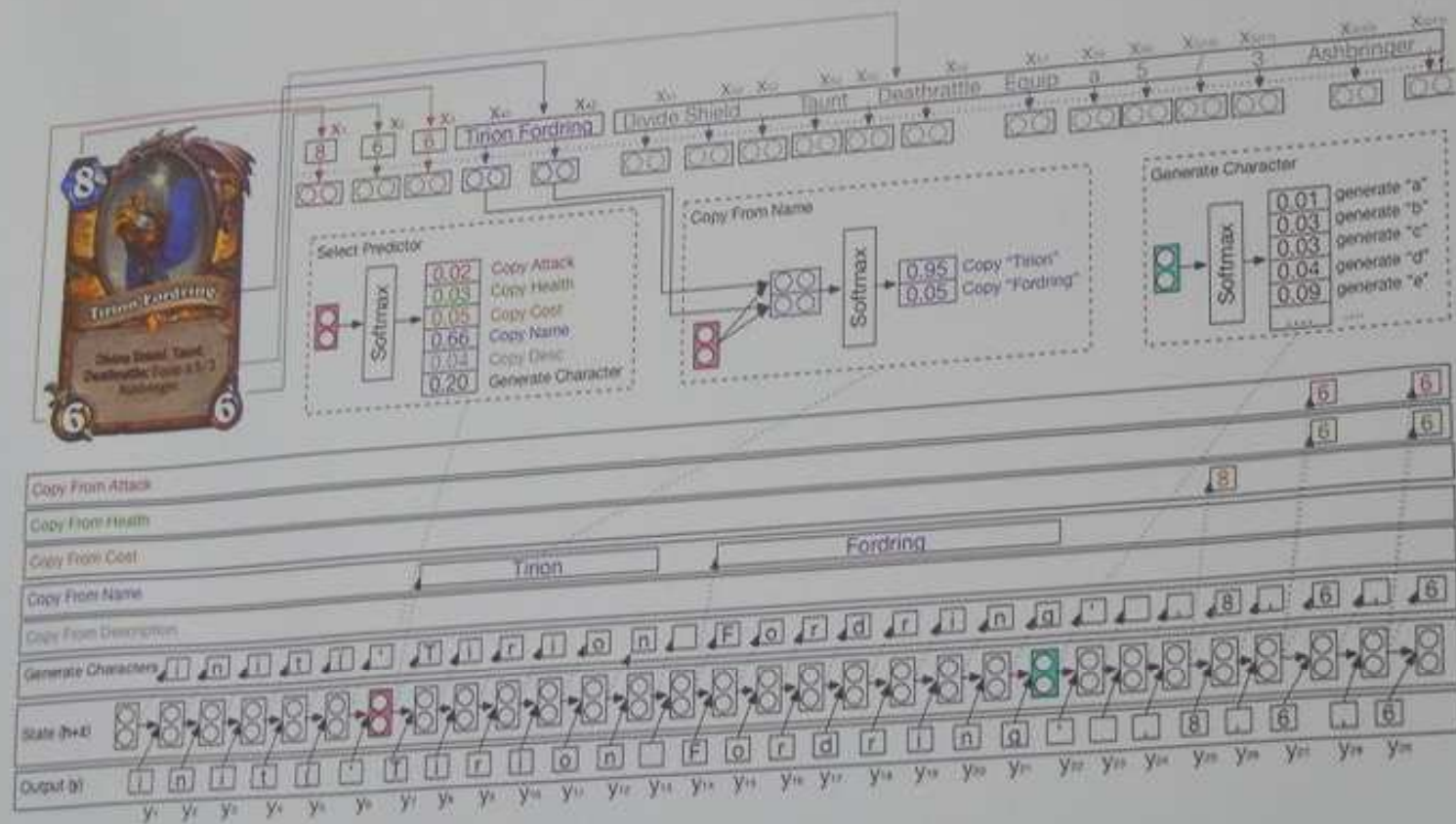
Magic the Gathering



Hearthstone

Ling et al., Latent Predictor Networks for Code Generation, ACL 2016

Latent Predictor Networks (Ling et al., 2016)



Text to Code



```
class MadderBomber(MinionCard): BLEU = 100.0
    def __init__(self):
        super().__init__("Madder Bomber", 5,
            CHARACTER_CLASS.ALL, CARD_RARITY.RARE,
            battlecry=Battlecry(Damage(1),
            CharacterSelector(players=BothPlayer(),
            picker= RandomPicker(6))))
```

```
def create_minion(self, player):$
    return Minion(5, 4)$
```



```
class Preparation(SpellCard): BLEU = 64.2
    def __init__(self):
        super().__init__("Preparation", 0,
            CHARACTER_CLASS.ROGUE, CARD_RARITY.EPIC,
            target_func=hearthbreaker.targeting.find_minion_spell_target)
```

```
def use(self, player, game):
    super().use(player, game)
    self.target.change_attack(3)
    player.add_aura(AuraUntil(ManaChange(-3),
        CardSelector(condition=IsSpell()), SpellCast()))
```


Seq2SQL (Zhong et al., 2017)

Question Input:

in what place did phil mickelson finish with a total of 282 ?



Seq2SQL Output:

SELECT finish FROM mytable WHERE total = 282 AND player = phil mickelson

Execution Result:

t16

Reinforcement Learning Reward:

Correct +1



データベース

実行

- 教師付き学習

+

- 強化学習

- 方策勾配法により、クエリの実行結果を報酬として学習

Database Table: mytable		year	t	s	sec	total	to	per	rank
player	country								
Tiger Woods	United States	1999 / 2000				270	-18		1
Shane Bieber	United States	2000				270	-12		2
Phil Mickelson	United States	2000				280	-6		716
David Lee	United States	2000				280	-6		716
David Lee II	United States	1997				280	-2		734
Rick Beem	United States	2000				281	+3		100
Bob Fink	United States	1998				286	+8		100

SQL Vocabulary:

SELECT WHERE FROM AND MAX MIN COUNT SUM AVG + - *

<https://einstein.ai/research/how-to-talk-to-your-database>

まとめ

- ニューラルネットワーク
 - リカレントニューラルネットワーク
 - 畳み込みニューラルネットワーク
- エンコーダー・デコーダーモデル
 - 系列から系列への変換
- 複雑なタスクを簡単なアーキテクチャで実現
 - レゴブロック (?) の組み合わせ、End-to-end 学習
- 大幅な精度向上
 - 構文解析、機械翻訳、質問応答、etc