BACHELOR THESIS

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Generating text from structured data

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Dedication.

Title: Generating text from structured data

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Abstract: In this thesis we examine ways of conditionally generating document-scale natural language text given structured input data. Specifically we train Deep Neural Network models on recently introduced RotoWire dataset containing statistical data about basketball matches paired with descriptive summaries. First, we analyse the dataset and propose several preprocessing methods (i.e. Byte Pair Encoding). Next, we train a baseline model based on the Encoder-Decoder architecture on the preprocessed dataset. We discuss several problems of the baseline and explore advanced Deep Neural Network architectures that aim to solve them (Copy Attention, Content Selection, Content Planning). We hypothesize that our models are not able to learn the structure of the input data and we propose a method reducing its complexity. Our best model trained on the simplified data manages to outperform the baseline by more than 5 BLEU points.

Keywords: text generation structured data natural language processing neural networks

Contents

Introduction

Language Modeling is the task of predicting what word comes next in the actual context. In this thesis we delve into a slightly more complicated task, into the Conditional Language Modeling, where the next generated word does not only depend on the context but also on some external factors.

Specifically we examine ways of conditionally generating document-scale texts given structured input data. We train Deep Neural Network models on recently introduced RotoWire dataset [Wiseman et al., 2017] which contains statistical information about basketball matches paired with professionally written summaries collected from RotoWire fantasy sports news website.

In chapter 1 we introduce the dataset, and reason about its characteristics. We show that the dataset is well suited for the task as the summaries are closely related to the input tabular data.

We follow up by collecting a set of statistics of the dataset. We propose several preprocessing methods which aim to simplify the learning path of the model, and show the resulting statistics of the preprocessed dataset (chapter 2).

Chapter 3 introduces several neural network architectures (Encoder-Decoder, Attention, Copy Mechanism) which serve as building blocks of the models prepared in chapter 4. The models are built incrementally following approaches of Wiseman et al. [2017] and Puduppully et al. [2019], starting with a baseline model and ending with Content Selection and Planning model.

Finally we present the experiments (chapter 5). Firstly, we discuss the evaluation of different aspects of the generated summaries (both automated and manual evaluation takes place). Next, we analyse the performance of the models prepared in chapter 4. We manage to improve from BLEU score 10 for the baseline model to 13.96 for the Copy model with Content Selection encoder. We hypothesise that the performance bottleneck of our approach is the complexity of the input tables and propose two methods aiming to simplify the inputs. We show that our best model trained on the simplified inputs outperforms the Copy model with Content Selection encoder in all the evaluated metrics.

All the models and preprocessing methods are developed in *python 3.8* and *tensorflow 2.4.1*. The implementation is discussed in appendix A.

1. Data

The goal of the thesis is to explore the possibilities of generating natural language representation of a sports match. The differences in the number of players, the environment, the rules etc. prevent us from creating one system for all the sports. In the introduction we stated that we narrowed the task to one particular sport, the basketball.

In this chapter we explain our requirements on the output summaries associated with the structured data, reason why we choose the RotoWire dataset, and elaborate on the format of the input tables.

1.1 Data requirements

We have high demands on the quality of the texts which are used as targets during training of the Deep Neural Network models. The summaries should be connected to statistical data about the match, and contain the least possible amount of subjective, emotional information. Otherwise the model wouln't have possibility to learn how to interpret its inputs, and instead it would learn how to generate some invaluable emotional phrases.

It is known that a lot of data is needed to train a deep neural network (e.g. Sennrich et al. [2016] trains the neural machine translation system on 4.2 million English-German sequence pairs). Therefore it's unfeasible to collect and prepare our own dataset, and we choose to select from a high variety of publicly available datasets.

We choose the RotoWire dataset [Wiseman et al., 2017]. It contains a set of statistics of NBA matches associated with summaries collected from the portal focused on fantasy sport news, `https://www.rotowire.com/basketball/`.

1.2 Summaries

In section 1.1 we have already discussed our demands on the summaries which will be used as targets.

Wiseman et al. [2017] experimented with one other summary origin, `https://www.sbnation.com/nba`, where articles are written by fans for fans. However such summaries do not meet our requirements (Wiseman et al. [2017] states that "many documents in the dataset focus on information not in the box- and line-scores") and the neural networks they trained on these kind of summaries "performed poorly".

Therefore we experiment only with the summaries from Rotowire fantasy sports news. In the following subsections we explain what is fantasy sport and why the summaries collected from Rotowire meet our expectations.

1.2.1 Fantasy sports

According to [Tozzi, 1999], the origins of the phenomenon of fantasy sports can be dated to the beginning of 1960s. The article tells a legend about a restaurant called La Rotisserie Francaise. There a group of ”sportswriters, accountants and lawyers” started the first fantasy sport league. Rotowire, which name is derived from the name of the restaurant, is the source of all the target summaries in the dataset.

Let’s proceed and discuss the rules of the fantasy sport according to Rotowire[1]. The fantasy league is created on top of a real world league, e.g. NBA. If you want to play, you choose a subset of NBA players and gain points based on their performance in the real-world NBA matches. You have limited resources and the better players cost more. The selection must contain a basketballer for each position (therefore it is not possible to draft e.g. 5 point guards and no power forward). The points are awarded according to the role, so that defensive and offensive players gain you points for different achievements in a match. The leagues differ in their specifics and we advise an interested reader to check the Rotowire fantasy league rules[1].

1.2.2 Fantasy sports news

To succeed in the fantasy sport, one must keep a good track of the player statistics and injuries, the tendencies of team performances, the trends causing the emergence of a future star or a burn-out. From the beginning there exists a form of news specializing directly on fantasy league players. `https://www.rotowire.com/` is one of the most popular ones. The articles tend to summarize the most important statistics as well as present a deeper understanding of the events that happened during the match. As noted by Wiseman et al. [2017], the articles are the ideal candidates for the target summaries of the structured data from the dataset.

1.3 Structured Data

The structured data is in form of multiple tables of statistics related to a particular NBA match. In this section we examine the tables.

To begin the examination, each datapoint contains a date when the match was played. This information isn’t leveraged in the summaries[2], therefore we opt not to use it.

1.3.1 Team Statistics

A datapoint contains a separate table with statistics, called the *line score*, for each of the opposing teams. Each *line score* contains 15 fields, some of which we will discuss in this section. The full listing can be found on the official github of the dataset [3]

Firstly there are fields with the team name and the city where the team is located.

[1] `https://www.rotowire.com/basketball/advice/`

[2] This isn’t technically true, as the majority of summaries contain a phrase like *”Team A defeated Team B on monday.”*, however since the date is in form *DD/MM/YYYY*, there isn’t any chance the network could deduce the day of the week from the date.

[3] `https://github.com/harvardnlp/boxscore-data`

Next there is a set of numerical statistics. We can divide them to the contextual statistics (the number of wins and looses prior to the actual match), the team-totals (*Team-total* means the overall team statistics. E.g. *TEAM-PTS* is the sum of all the points scored by the players of the team), and the per-period point statistics (*TEAM-PTS_QTR1* - *TEAM-PTS_QTR4*). Table 1.1 shows a portion of both *line scores* present in the first data-point from the development part of the RotoWire dataset.

Name	City	PTS_1	AST_2	REB_3	TOV_4	Wins	Losses	...
Raptors	Toronto	122	22	42	12	11	6	...
76ers	Philadelphia	95	27	38	14	4	14	...

Note: The statistics are accumulated across all the team players

$_1$ Points; $_2$ Assists; $_3$ Rebounds; $_4$ Turnovers

Table 1.1: An example of the team statistics from the development part of the Rotowire dataset

1.3.2 Player statistics

The player statistics are gathered in a table called *box score.* In each row there is an information about the player name, the city he plays for (since there are 2 teams originating in Los Angeles, the distinction is made by calling one *LA* and the other one *"Los Angeles"*), his position on the starting roster (or the *N/A* value if he isn't in the starting lineup), and another 19 fields with statistics summing up the impact of the player in the match (e.g. points, assists, minutes played etc.). Again, the full listing can be found on github[3] and table 1.2 contains a portion of a *box score* from the first data-point from the development part of the RotoWire dataset.

Name	Team City	S_POS_1	PTS_2	STL_3	BLK_4 ...
Kyle Lowry	Toronto	G	24	1	0 ...
Terrence Ross	Toronto	N/A	22	0	0 ...
Robert Covington	Philadelphia	G	20	2	0 ...
Jahlil Okafor	Philadelphia	C	15	0	1 ...

Note: N/A means that the statistic couldn't be collected because it is undefined
(e.g. player didn't appear on starting roster therefore his starting position is undefined)

$_1$ Starting position ; $_2$ Points; $_3$ Steals; $_4$ Blocks

Table 1.2: An example of the player statistics from the development part of the Rotowire dataset

1.4 Relation of summaries and tables

In this section we would like to show the relationship between the structured data and the target summary. Let's observe the data-point from the development part of the dataset in figure 1.1. The non-highlighted text shows one-to-one correspondence with the structured data. The blue-highlighted text marks the information which is present in the input data only implicitly. However the level of implicitness varies. It is relatively easy to see that since Terrence Ross's starting position is ”N/A”, he must have started off the bench. On the other hand the fact that ”The Raptors came into this game as a monster favorite” requires comparison of the winning-loosing records of both teams. The yellow-highlighted text labels the information that isn't deducible from the input data and the network would have to learn to hallucinate to be able to generate such text.

Somebody may argue that the observations do not sound favorable for the dataset. We see it as a big challenge and a possibility to apply advanced preprocessing as well as interesting architectural design of the neural networks. We will further elaborate on the issue of too noisy data in section 2.7.

TEAM	WIN	LOSS	PTS$_1$	FG_PCT$_2$	REB$_3$	AST$_4$	...
Raptors	11	6	122	55	42	22	
76ers	4	14	95	42	38	27	

PLAYER	City	PTS$_1$	AST$_4$	REB$_3$	FG$_5$	FGA$_6$	S_POS$_7$	...
Kyle Lowry	Toronto	24	8	4	7	9	G	
Terrence Ross	Toronto	22	0	3	8	11	N/A	
Robert Covington	Philadelphia	20	2	5	7	11	G	
Jahlil Okafor	Philadelphia	15	0	5	7	14	C	
DeMar DeRozan	Toronto	14	5	5	4	13	G	
Jonas Valanciunas	Toronto	12	0	11	6	12	C	
Ersan Ilyasova	Philadelphia	11	3	6	4	8	F	
Sergio Rodriguez	Philadelphia	11	7	3	4	7	G	
Richaun Holmes	Philadelphia	11	1	9	4	10	N/A	
Nik Stauskas	Philadelphia	11	2	0	4	9	N/A	
Joel Embiid	Philadelphia	N/A	N/A	N/A	N/A	N/A	N/A	
...								

The host Toronto Raptors defeated the Philadelphia 76ers , 122 - 95 , at Air Canada Center on Monday . The Raptors came into this game as a monster favorite and they did n't leave any doubt with this result . Toronto just continuously piled it on , as they won each quarter by at least four points . The Raptors were lights - out shooting , as they went 55 percent from the field and 68 percent from three - point range . They also held the Sixers to just 42 percent from the field and dominated the defensive rebounding , 34 - 26 . Fastbreak points was a huge difference as well , with Toronto winning that battle , 21 - 6 . Philadelphia (4 - 14) had to play this game without Joel Embiid (rest) and they clearly did n't have enough to compete with a potent Raptors squad . Robert Covington had one of his best games of the season though , tallying 20 points , five rebounds , two assists and two steals on 7 - of - 11 shooting . Jahlil Okafor got the start for Embiid and finished with 15 points and five rebounds . Sergio Rodriguez , Ersan Ilyasova , Nik Stauskas and Richaun Holmes all finished with 11 points a piece . The Sixers will return to action on Wednesday , when they host the Sacramento Kings for their next game . Toronto (11 - 6) left very little doubt in this game who the more superior team is . Kyle Lowry carried the load for the Raptors , accumulating 24 points , four rebounds and eight assists . Terrence Ross was great off the bench , scoring 22 points on 8 - of - 11 shooting . DeMar DeRozan finished with 14 points , five rebounds and five assists . Jonas Valanciunas recorded a double - double , totaling 12 points and 11 rebounds . The Raptors next game will be on Wednesday , when they host the defensively - sound Memphis Grizzlies .

Note: $_1$ Points; $_2$ Field Goal Percentage; $_3$ Rebounds; $_4$ Assists; $_5$ Field Goals; $_6$ Field Goals Attempted; $_7$ Starting Position; *N/A* means undefined value

Figure 1.1: A data-point from the development part of the Rotowire dataset. Yellow-highlighted text isn't based on the input data. Blue-highlighted text implicitly follows from the input data.

2. Preprocessing and Statistics of the Dataset

To generate text from structured data we choose the Deep Neural Networks and specifically the Encoder-Decoder (ED) neural architecture (chapter 3). The ED is suited to process sequential one dimensional data, however we cope with two dimensional tables. In this chapter we present the statistics of the dataset *before any preprocessing.* Next we elaborate about the methods of preprocessing and cleaning of the data. In the end we show the statistics of the dataset with all the transformations applied.

2.1 Transforming Tables to Records

At first let's define a table. A table is a two dimensional data structure, where the information is stored not only in the actual values in cells, but also in the positional information. Values in the same column have the same type, whereas values in the same row belong to the same entity. An example of a table as we have defined it is in figure 2.1.

	type$_1$	type$_2$ ...
entity$_1$	value$_{1,1}$	value$_{1,2}$ ...
entity$_2$	value$_{2,1}$	value$_{2,2}$ ...
...		

Table 2.1: An example of structured data

We use the same notation as Liang et al. [2009]. Table $\mathcal{T}$ is transformed into a sequence of records $\mathbf{x} = \{r_i\}_{i=1}^{J}$, where r_i denotes i-th record. To fulfill our goal of keeping the most of the positional information from the table, each record contains field *r.type* denoting the type of the value, the actual value *r.value* and the entity *r.entity* to which the record belongs. At the end, we transform table 2.1 to a sequence of records shown in figure 2.1.

{*type*: type$_1$; *entity*: entity$_1$, *value*: value$_{1,1}$}

{*type*: type$_2$; *entity*: entity$_1$, *value*: value$_{1,2}$}

{*type*: type$_1$; *entity*: entity$_2$, *value*: value$_{2,1}$}

...

Figure 2.1: An example of records obtained by transforming table 1.1

2.2 Dataset Statistics

We believe that the challenges posed by the RotoWire dataset can be summarized in a set of statistics. In this section we want to present the most important ones to help reader to understand the nature of the problem.

Firstly, Wiseman et al. [2017] notes that the target summaries as well as the sequences of input records are really long compared to other datasets modelling the data-to-text task (e.g. WikiBIO [Lebret et al., 2016] contains 13-times smaller gold summaries and 32-times smaller input tables, Wiseman shows a comparison to some other datasets as well).

Secondly, many words occur rarely and the generation system cannot learn a good representation of them (it is known as a *rare word problem*). It should be noted that the problem can be resolved by the means of clever preprocessing (section 2.6) or with help of advanced neural architectures (section 3.3).

Thirdly, there are many values which represent facts, e.g. values that cannot be deduced from the context (e.g. points a player scored in a match etc.) but must be selected and copied from the table.

The original dataset as prepared by Wiseman et al. [2017], is already divided to train (3398 samples), development (727 samples) and test (728 samples) sets. *In the statistics presented below we state that there are only 3397 samples in the train set because one of the samples is the famous Lorem Ipsum template.*

2.2.1 Length-wise Statistics

The input tables contain huge amount of information. 2 teams and up to 30 players participate in a match of basketball. After transformation to a sequence, a player is represented by 24 and a team by 15 records. The type field *r.type* is the only trait distinguishing the team and player records. Table 2.2 summarizes the length statistics of the input sequences.

Set	Max Number of Records	Min Number of Records	Avegage Number of Records	Size
train	750	558	644.65	3397
development	702	582	644.66	727
test	702	558	645.03	728

Table 2.2: Statistics of tables as used by Wiseman et al. [2017]

There is much greater variance in the lengths of output summaries. The longest sequence of input records is 1.34 - times longer than the shortest one, while the factor between longest and shortest summaries is more than 5. The size of inputs and outputs places high memory and computation demands on the GPUs used for training, and needs a special treatment (as will be explained in section 4.1).

2.2.2 Occurrences of Unique Tokens

While the length of the inputs and the outputs increases computational demands, another common issue is the *rare word problem.* If a token appears only sporadi-

Set	Max Summary Length	Min Summary Length	Avegage Summary Length	Size
train	762	149	334.41	3397
validation	813	154	339.97	727
test	782	149	346.83	728

Table 2.3: Statistics of summaries as used by Wiseman et al. [2017]

cally in the train data, the generation system can't recognize how to use it. After discussions with my advisor we think it is reasonable to expect that the system should learn a good representation of a token if it appears at least 5 times in the train set.

There is about 11 300 unique tokens in the dataset (in the union of train, development and test set). In table 2.4 We present the statistics regarding the occurrences of the unique tokens. We can see that only 42 % of all the unique tokens appear at least 5 times in the train part of the dataset.

However we expect that even if some anomaly in the real word happens (e.g. team scores 200 points, although at the time of writing no team in the history of NBA scored more than 186) the system should be able to simply *copy* the value of *TEAM-PTS* record without reasoning about the actual value. Consequently we are interested in tokens that cannot be copied from the table. Since most of the named entities are directly copiable, there is no need to preserve casing. All the aforementioned statistics are summarized in table 2.4.

In the end we see that under our assumptions about 60 % of all the unique tokens cannot be learned by the generation system.

Set	Unique Tokens	>= 5 Absolute	>= 5 Relative
train	9779	4158	42.52%
train_wop$_1$	8604	3296	38.31%
train_wopl$_2$	8031	3119	38.84%

Note: $_1$ train_wop is training set with all the player names, city names, team names and numbers extracted $_2$ train_wopl is train_wop lowercased

Table 2.4: Occurrences of tokens in summaries from dataset RotoWire

In table 2.5 we can see how many of the unique tokens learned during training can be found in the respective development and test datasets. Under our assumptions we can expect the generated text to share less than 65 % of the vocabulary with the gold references.

2.3 Transformations of Input Tables

Firstly we want to present what kind of data is stored in the input tables, and how it is preprocessed. After that we show the final format of a record which is fed to the generation system.

Set	**Unique Tokens**	**Train Overlap**	**Train$_{>=5}$ Overlap**
valid	5625	88.18%	66.63%
test	5741	87.46%	65.72%
valid_wop$_1$	4714	86.36%	61.92%
test_wop$_2$	4803	86.03%	61.13%
valid_wopl$_3$	4442	86.74%	62.36%
test_wopl$_4$	4531	86.32%	61.37%

Note: train$_{>=5}$ overlap is a set of all the tokens from the development/test dataset with more than 5 occurrences in the train dataset summaries $_1$, $_2$, $_3$, $_4$ have the same meaning as in table 2.4

Table 2.5: Overlap of train dataset summaries and valid/test dataset summaries

2.3.1 Tabular Types

There are 39 types (different headers of columns as discussed in section 2.1). A type is associated to textual or integer value which describes either a team or an individual. There are only 7 types bound to textual values, out of which 2 are related to teams (*TEAM-NAME*, *TEAM-CITY*) and 5 to individuals (*FIRST_NAME**, *SECOND_NAME**, *PLAYER_NAME**, *START_POSITION**, *TEAM_CITY**)

2.3.2 Numerical values

The other 32 types desribe absolute (*TEAM-PTS*[1], *FTM*[2] ...) or relative integer values (*TEAM-FT_PCT*, *FT_PCT*[3], ...). During preprocessing no changes are made to any tabular numerical value[4].

2.3.3 Textual values

Regarding the textual values, we consider each as a single token. Since the names of teams are already one word long (with one exception needing a transformation *Trail Blazers* $\rightarrow$ *Trail_Blazers*) the transformation is rather trivial. The similar observation applies to names of cities (with 6 exceptions: *Oklahoma_City*, *San_Antonio*, *New_Orleans*, *Los_Angeles*, *Golden_State*, *New_York*), and start positions.

Out of three types connected to player credentials, only *PLAYER_NAME* (describing player full name with all the attributes e.g. *Johnny O'Bryant III*) is multi-token.

The original take on the problem is different to ours. The authors of the dataset [Wiseman et al., 2017], as well as the authors of one of the more successful approaches to the task [Puduppully et al., 2019] make use of three special types, *PLAYER_NAME*, *FIRST_NAME* and *SECOND_NAME* which allow to

[1]Team Points

[2]Number of converted free throws by an individual, *"free throws made"*

[3]*team/player free throw percentage*

[4]Wiseman et al. [2017] already converted all the relative values to integers. We don't consider this as a preprocessing since only the converted values are available in the dataset.

distinguish if *James* refers to the first name of star player *James Harden* or to a second name of the legend of *LeBron James*.

Our approach is based on the idea that if only one token is associated to an entity then the generation system has easier job in learning what to copy. Therefore we transform the name of each player to a single token. To make copying possible a preprocessing of the output summaries as described in 2.4.2 must take place.

Consequently *FIRST_NAME* and *SECOND_NAME* records aren't needed anymore. Number of records belonging to a particular player is thus reduced from 24 to 22 and the overall number of records which describe one match is decreased by 8% (the maximal length of a table decreases from 750 to 690).

2.3.4 Entities

The type information tells us what the number or text in the value field represents. However it is the entity field (the row in table 2.1) which brings together all the records describing the same player or team. Let's show an example of records about a star player, *Stephen Curry.* His name is stored in a record of type *PLAYER_NAME*, and value *Stephen_Curry.* To link all the information about him together, each record has an entity field labelled *Stephen_Curry.* Similarly all the records connected to a team with name ***A*** have the same entity field, ***A***.

At last, we should notice that the overall team information is the union of the accumulated team stats (e.g. the number of points scored by all the players of a team) and the collection of statistics of the individuals playing for the team. Therefore the record also contains *HOME/AWAY* field which brings together all the statistics about the home side and the away side.

2.3.5 Record Format

The records fed into the generation system contain the following fields:

- *Type*
- *Value*
- *Entity*
- *Home/Away flag*

2.3.6 Order of Records

The generation system should be able to understand the meaning of a record and shouldn't rely on a specific organization of the table. This is modelled by emplacing the team records at the end, so that the system will need to search for the team statistics. Since the size of the input sequence isn't uniform, the team records can start anywhere between 500th and 720th record.

However during experiments we found out that the models we train have problems with extraction of information from the input table. Therefore we prepared two additional schemes of organization of the input records.

Ordered records

The first scheme is rather simple. We place the 15 home team records at the beginning of the ordered sequence followed by 15 away team records. The remaining N sequences of 22 records related to players are ordered according to their points-total in the corresponding match.

Shortened records

The second scheme leverages an observation about the output summaries. We can see that only few best players are thoroughly discussed and the information about the remaining ones is reduced to mentioning their point totals.

Therefore we order the records in the same way as previously. Only first 10 players according to their point-totals are mentioned. The information about top three players is reduced from 22 to 21 records (we cut off the information about starting position) and the information about the remaining players is reduced from 22 to 5 records (minutes they played, points and assists they scored, their team and name). The maximal size of the newly constructed sequence is 130 records (compared to 690, the size of table after transformations described in section 2.3.3).

{*type*: PTS; *entity*: Stephen_Curry, *value*: 25; *ha*: HOME }

{*type*: TEAM-PTS; *entity*: Warriors, *value*: 122; *ha*: HOME}

. . .

Figure 2.2: An example of a player and a team record.

2.4 Preprocessing of Summaries

We would like to reiterate that our motivation is to avoid the *rare word problem* and to make copying words from the sequences of input records as easy as possible. Therefore we opt for methods which reduce the number of tokens, increase their average frequency (because the system couldn't learn the most sporadic ones anyway), and transform the tokens describing the tabular data to the same form as is used in the table (so copying is trivial).

2.4.1 Number Transformations

Just as Wiseman et al. [2017] and Puduppully et al. [2019], we represent the numbers only by numerals. This preprocessing method partially fulfills both of our goals. Obviously it decreases the unique token count, but on top of that it makes copying easier. E. g. the sentence *"Isaiah Thomas once again excelled , scoring 23 points,* ***three*** *assists and* ***three*** *rebounds."* is transformed to *"Isaiah Thomas once again excelled , scoring 23 points,* ***3*** *assists and* ***3*** *rebounds."*. Under this setting, the network still has to learn the correspondence between record type and the summary token *"AST"* $\cong$ *"assists"* but without the need of linking *"three"* to *"3"* the connection of the phrase with record {*AST; 3; Isaiah_Thomas; Home*} should be much clearer. However we preserve the word *"three"* when it forms a part of a basketball terminology (e.g. *three pointer*) to differentiate between these different meanings of the word. The transformations are done with the help of the *text2num* library[5] which is also used by the authors cited above.

2.4.2 Player name transformations

The generation system should be able to create a summary of player's actions in the game based on the records describing his match-statistics. It is common that at first a player is mentioned by his full name (e.g. *Stephen Curry*) and after that only by his second name (*Curry*). Also more than 97 % of all the players have exactly 2 names (first, last). This leaves out 17 players with longer names the most extreme case being *Luc Richard Mbah a Moute*, who is represented in the whole dataset by 6 different combinations of ellipsis in his name.

Since only the full name concatenated to a single token is contained in the input records we created a simple algorithm which transforms all [6] the references to a player to that specific token.

We haven't measured the accuracy of the algorithm, however it passes an eye-test as during the development of neural models we have inspected a great amount of produced summaries which haven't contained any discrepancies.

At first we gather all the player names from the input tables. The transformation then happens in three steps, which are described on the example sentence from figure 2.3.:

- **1. Extraction of player names from the summary**
  The summary is at first divided to sentences, using NLTK [7] library. Then we traverse each sentence and extract the longest subsequences of tokens which appear in the set of the player names. This way, one-token name *James* and two-token name *James Harden* is extracted. (Although *James Harden* hasn't played in the game and therefore the network cannot learn to copy his name, we extract it to densify the data, so the player is represented by the same token in all the summaries)

- **2. Resolution of one-token references and creation of transformation dictionary**
  James Harden is a two-token name matched in the first phase, so we assume that it is already full name of the player and we add a trivial transformation *James Harden* → *James_Harden.* *James* is a one-token name which needs resolution. At first we look if anyone whose second (third . . .) name is *James* hasn't already been mentioned in the summary. If not we proceed to searching through all the players in the match statistics. There we spot *LeBron James* and add the transformation *James* → *LeBron_James.* Note that we create a unique transformation dictionary for each summary and we assume, that no player is called only by his first name.

[5]https://github.com/allo-media/text2num

[6]Although technically speaking this is not true as it doesn't transform any pronouns and the transformations follow simple path: *some part of a name* → *full name*

[7]https://www.nltk.org/

- **3. Application of transformations**
  The summary is traversed for the second time and the longest subsequences appearing in the transformation dictionary are substitued.

While King James struggled , James Harden was busy putting up a triple - double on the Detroit Pistons on Friday.

↓

While King LeBron_James struggled , James_Harden was busy putting up a triple - double on the Detroit Pistons on Friday.

Figure 2.3: Example of transformation of player names leveraging the knowledge of players on the rosters as well as of all players from the train set.

2.5 Vocabularies

During preprocessing we collect the vocabulary of all the words from the training set. Each token is represented as an index to the vocab. This representation is fed to the initial layers of the neural network (embedding layers which will be discussed in section 3). Therefore the network learns to process only the tokens belonging to the vocabulary and no new tokens can be introduced during inference.

We collect 3 different vocabularies, one for record types, one for home/away flags and one for all the entities, number values and tokens from the summaries.

2.6 Byte Pair Encoding

The Byte Pair Encoding (BPE) [Sennrich et al., 2016] is a method of preprocessing of a text. It was developed to enable the Neural Machine Translation models to operate on subword units. It allows them to generate and accept sequences of subwords and thus handle words unseen during training. (E.g. there are words 'high', 'low', 'lower' in the training dataset, therefore under regular setting the network couldn't be able to generate or process word 'higher'. When operating on subwords 'high', 'low', 'er' this isn't an issue anymore since the network can learn to chain subwords 'high', 'er' to form the word unseen during training.)

Since in NBA there is a fixed set of cities, teams and players (only about 10 players from development and 10 from test set were unknown from training) this isn't our main concern. However we can use the BPE to lower the size of the summary token vocabulary (E.g. looking at the previous example, even if the word 'higher' had been a part of the input vocabulary, the vocabulary of subwords would have still contained only subwords 'high', 'low', 'er'.) Thus the average frequency of a token increases as well as the generational capacity of the network.

In this section we begin with a short explanation of the algorithm and conclude with the statistics of the fully transformed dataset.

2.6.1 Algorithm

We use the implementation of the algorithm from the authors of the BPE paper[8], which is also downloadable as a standalone python package. The idea is to divide each token from the train set to characters, and add it to the *symbol vocabulary*. Iterating over the text each time we merge together the most common pair of succeeding characters to create a new symbol. The symbol is added to the vocabulary and each occurrence of the pair is substitued by it. At the end (after N iterations, where N is the hyperparameter of the algorithm), the symbol vocabulary contains all the characters and newly created symbols.

In practice it is more efficient to create a token vocabulary (tokens are weighted by the number of occurrences in the corpus), and iterate over it instead of over the whole corpus. Also to allow easy detokenization to the original text, a special <*eow*> token is appended to each token. An excerpt from the original paper shows the minimal possible implementation of such approach 2.6.

At the test time the text is divided to characters and the longest subsequences of characters appearing in the symbol vocabulary are transformed to the corresponding symbol.

2.6.2 Application

As stated previously, the BPE should transform the output summaries to a sequence of subwords. However, in certain situations it may be contraproductive. E.g. it may make copying harder by dividing single-token player name to multiple tokens. Therefore we apply the BPE to all the tokens except the ones which correspond to player/city/team names and numerical values. We set the number of iterations to 2000, which means that the overall vocabulary contains around 2800 tokens (there is about 700 players, 29 cities and 30 teams). An example of the final appearance of a summary after all the transformations mentioned in the chapter can be seen in figure 2.4.

the host Toronto Raptors defeated the Philadelphia 76ers , 122 - 95 , at air canada center on monday . the Raptors came into this game as a monster fav⋆ or⋆ ite and they did n't le⋆ ave any doub⋆ t with this result . Toronto just continu⋆ ou⋆ s⋆ ly pi⋆ led it on , as they won each quarter by at least 4 points . the Raptors were l⋆ ights - out shooting , as they went 55 percent from the field and 68 percent from three - point range . they also held the sixers to just 42 percent from the field and dominated the defensive rebounding , 34 - 26 . fas⋆ t⋆ break points was a huge difference as well , with Toronto winning that battle , 21 - 6 . Philadelphia (4 - 14) had to play this game without Joel_Embiid (rest) and they cle⋆ arly did n't have enough to compe⋆ te with a poten⋆ t Raptors squad . Robert_Covington had 1 of his best games of the season though , tallying 20 points , 5 rebounds , 2 assists and 2 steals on 7 - of - 11 shooting . . . .

Figure 2.4: A part of transformed summary corresponding to the sample from figure 1.1. ⋆ is used to mark that the following token formed the same word in the original text. Note that in the original implementation @@ is used instead.

[8] `https://github.com/rsennrich/subword-nmt`

2.7 Cleaning

During implementation of the Content Planning approach (discussed in section 4.4.2) we found out that the authors of the method, [Puduppully et al., 2019], have used only subset of training and validation data. They removed all the pairs summary-table where the "gold" summary contained information which wasn't linked to the input table. Figure 2.5 shows an example of such a summary.

We use a subset of the subset used by Puduppully. In addition we also removed all the samples from the dataset about matches between teams from Los Angeles (Clippers and Lakers) where the distinction between different teams is not shown, and every player is listed as playing for "Los Angeles" (thus it is impossible to tell if he played for Clippers or Lakers).

After removing all the non-valid pairs, the dataset size was reduced to 3369 train, 721 development and 727 test samples.

There exist datasets based on RotoWire, which contain cleaner data and summaries corresponding better to input tables [Wang, 2019], [Thomson et al., 2020]. However we choose to continue with the RotoWire dataset, as we are already accustomed to the format of the data.

> Following a week filled with trade rumors , Paul George came out of the All-Star break in fairly unimpressive fashion . In his first 4 games following the break , Paul George shot a combined 16 - of - 54 (29 percent) from the field and was averaging just 14 points per game over that stretch . However , in his last 2 games , Paul George has flipped the script entirely and rattled off a pair of incredible offensive performances . Following Monday 's 36 - point performance in the Pacers ' loss to the Hornets , Paul George has now scored a combined 70 points over his last 2 games and did so while shooting a scorching 27 - of - 44 (61 percent) from the field and 12 - of - 23 (52 percent) from behind the arc . The performances from Paul George on Sunday and Monday were by far his best back - to - back shooting and scoring performances of the season .

Figure 2.5: An example of a faulty summary. To illustrate how hard it is to tell even which teams played we purposely do not show the input table.

2.8 Statistics of Transformed Dataset

In this section we want to summarize all the transformations applied to the summaries and tables and present the statistics of the summaries after transformations.

At first we converted all the tokens in the value and entity fields of a record to a single token. Next we transformed all the numerical values in the summaries to numerals and all the player names to a single token to allow direct copying from the input records. At the end we applied the Byte Pair Encoding to all the remaining tokens to decrease the overall number of tokens and increase the average frequency of a token.

In table 2.6 we can observe that almost 90 % of all the tokens occur more than 5 times therefore we can conclude that data is definitely much denser (compared to 42 % in the original data 2.4). As a nice side effect the intersection of development/test set and train set is almost 99 % (table 2.7). It is clear from figure 2.4 that each factual information is represented by a single token and can be copied as is from the *r.value* field of a record.

Set	**Unique Tokens**	>= 5 **Absolute**	>= 5 **Relative**
train	2839	2531	89.15%

Table 2.6: Occurrences of tokens in transformed summaries from dataset RotoWire

Set	**Unique Tokens**	**Train Overlap**	**Train**$_{>=5}$ **Overlap**
valid	2582	98.80%	95.70%
test	5741	98.69%	95.45%

Table 2.7: Overlap of transformed train dataset summaries and valid/test dataset summaries

Tables 2.8, 2.9 show that while the lengths of input records decreased (mainly because of player name transformations discussed in section 2.3.3), the lenghts of output summaries increased (due to byte pair encoding).

Set	**Max Number of Records**	**Min Number of Records**	**Avegage Number of Records**	**Size**
train	690	514	593.41	3369
development	646	536	593.40	721
test	646	514	593.77	727

Table 2.8: Length statistics of the preprocessed tables.

Set	**Max Summary Length**	**Min Summary Length**	**Avegage Summary Length**	**Size**
train	826	148	351.41	3397
validation	847	150	357.73	727
test	805	146	364.50	728

Table 2.9: Lenght statistics of the preprocessed summaries.

```python
import re, collections

def get_stats(vocab):
    pairs = collections.defaultdict(int)
    for word, freq in vocab.items():
    symbols = word.split()
    for i in range(len(symbols)-1):
        pairs[symbols[i],symbols[i+1]] += freq
    return pairs

def merge_vocab(pair, v_in):
    v_out = {}
    bigram = re.escape('␣'.join(pair))
    p = re.compile(r'(?<!\S)' + bigram + r'(?!\S)')
    for word in v_in:
        w_out = p.sub(''.join(pair), word)
        v_out[w_out] = v_in[word]
    return v_out

vocab = {'l␣o␣w␣</w>' : 5, 'l␣o␣w␣e␣r␣</w>' : 2,
             'n␣e␣w␣e␣s␣t␣</w>':6, 'w␣i␣d␣e␣s␣t␣</w>':3}
num_merges = 10
for i in range(num_merges):
    pairs = get_stats(vocab)
    best = max(pairs, key=pairs.get)
    vocab = merge_vocab(best, vocab)
    print(best)
```

OUTPUT:

```
r ·    → r·
l o    → lo
lo w   → low
e r ·  → er·
```

Figure 2.6: Python code extracted from paper **Neural Machine Translation of Rare Words with Subword Units** by Sennrich et al. [2016] Output represents the learned merge operations.

3. Neural Network Architectures

In previous chapter (2) we have shown how to transform the structured tabular data into a sequence of records, therefore we have reduced the problem to an instance of the famous sequence to sequence problem. Now, we show how to create a system that transforms the input sequential data (structured records) to the output sequential data (natural language).

The most common way to tackle the sequence to sequence problem is to use the Encoder-Decoder architecture proposed by Sutskever et al. [2014]. It is the main approach we used throughout this thesis. In this chapter we introduce the concepts behind the encoder-decoder architecture, its shortcomings (fixed vocabulary and thus problems with generation of words unseen during training, divergence and hallucinations) and ways to overcome these shortcomings (the attention mechanism, the copy mechanisms, the further transformations of input sequences). Since it is not the purpose of this work, only the basics of the concepts are presented, and we provide links to papers, books and tutorials which helped the author on his path to understanding.

Notation

Many papers diverge on the notation and naming conventions of the architectures. Therefore we choosed to adopt the notation used in *Tensorflow Keras API, version 2.x* [Abadi et al., 2015]. Specifically in the field of recurrencies it is discutable if the paper refers to *tf.keras.layers.RNNCell* or to *tf.keras.layers.RNN*. we believe that they can be used interchangeably in the context of this chapter, hence we (rather deliberately) choose the latter notation (*without 'Cell'*).

A Note About Embeddings

"An embedding is a low-dimensional, learned continuous vector representation of discrete variables into which you can translate high-dimensional vectors." [Daylor, 2019]. In this work we do not experiment with pretrained word embeddings, and we tune only the embedding-dimension hyperparameter of *tf.keras.layers.Embedding* layer.

3.1 The Encoder-Decoder Architecture

Proposed by Sutskever et al. [2014] the Encoder-Decoder is composed of 2 recurrent units, called Encoder and Decoder. In this section we briefly introduce the Recurrent Neural Network (*tf.keras.layers.SimpleRNN*), its modification, the Long Short-Term Memory (*tf.keras.layers.LSTM*) [Hochreiter and Schmidhuber, 1997] and the high-level overview of the Encoder-Decoder architecture.

3.1.1 Recurrent Neural Network

Let $\boldsymbol{x} = (x^{(1)}, \ldots, x^{(t)})$ be the input. The standard Feed-Forward Network (*tf.keras.layers.Dense*) has a different set of weights for each input time-step $x^{(t)}$, therefore the number of time-steps of the input needs to be known in advance.

The Feed-Forward Neural Network

$$\boldsymbol{y} = activation(W\boldsymbol{x} + b) \tag{3.1}$$

On the contrary, the Recurrent Neural Network (RNN) [Rumelhart et al., 1988] (*tf.keras.layers.SimpleRNN*) shares the same set of weights between time-steps and in addition it keeps a hidden state. At each time-step the hidden state is updated and used to calculate the output as in equation 3.2. The computation can be visualized either as a loop, or as a feed-forward network with shared weights 3.1.

The Recurrent Neural Network

$$\begin{aligned} h_t &= f_h(x_t, h_{t-1}) \\ y_t &= f_t(h_t) \end{aligned} \tag{3.2}$$

Note: h_t is the hidden state; y_t is the output at t-th timestep; tf.keras.layers.SimpleRNN uses $f_t \cong id$ and $f_h \cong tanh$ as default.

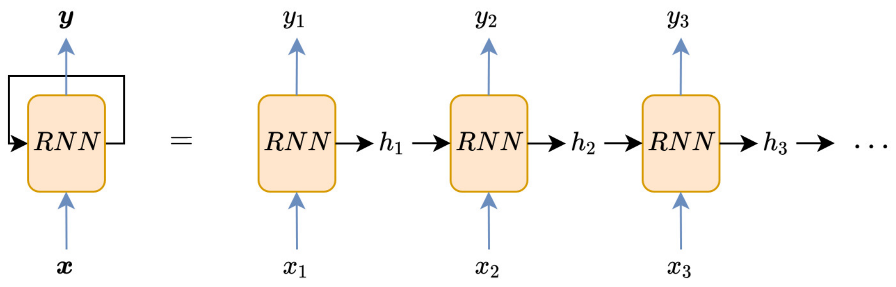


Figure 3.1: Visualizations of the RNN

The network is trained by back-propagation through time (BPPT) [Werbos, 1990]. It has been shown that the RNN suffers from vanishing / exploding gradient problems [Hochreiter and Schmidhuber, 1997].[1] Which cause that either the RNN cannot learn anything or it is really unstable. These difficulties are adressed by more sophisticated architectures such as Gated Recurrent Unit[2] [Cho et al., 2014b] or Long Short-Term Memory [Hochreiter and Schmidhuber, 1997].

3.1.2 Long Short-Term Memory

The Long Short-Term Memory (*tf.keras.layers.LSTM*) addresses the vanishing gradient problem. It does so by adding a special cell state for capturing long range context and series of gating mechanisms. The latter update the cell state and regulate the flow of gradient through the network (as shown in figure 3.2). The more in-depth explanation can be found in [Olah, 2015].

[1]We believe that discussion about BPPT and exploding/vanishing gradient problems is beyond the scope of this work. Therefore we refer the reader craving for further explanation to [Goodfellow et al., 2016] and to referenced papers.

[2]Although it is one of the most known architectures we used only LSTM for our experiments.

$$y_t = W_{hy}h_t + b_y \tag{3.3}$$
$$h_t = o_t tanh(c_t) \tag{3.4}$$
$$o_t = \sigma(W_o[h_{t-1}; x_t] + b_o) \tag{3.5}$$
$$c_t = f_t * c_{t-1} + i_t * tanh(W_c[h_{t-1}; x_t] + b_c) \tag{3.6}$$
$$i_t = \sigma(W_i[h_{t-1}; x_t] + b_i) \tag{3.7}$$
$$f_t = \sigma(W_f[h_{t-1}; x_t] + b_f) \tag{3.8}$$

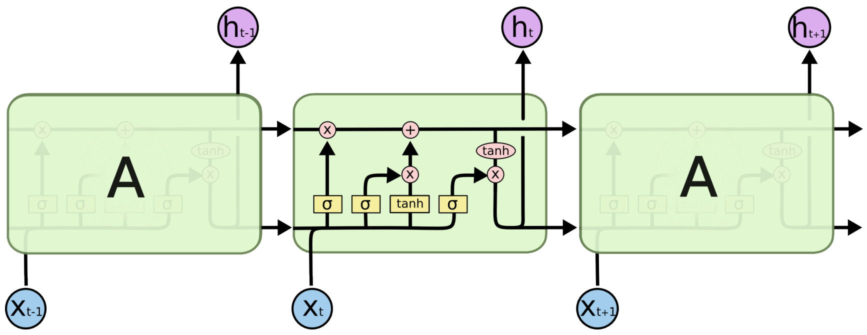


Figure 3.2: Visualization of LSTM [Olah, 2015]

3.1.3 High-level Overview of Encoder-Decoder Architecture

As stated by Sutskever et al. [2014], the main goal of the encoder-decoder architecture is to estimate the conditional probability $p(y_1, \ldots, y_n | x_1, \ldots, x_m)$ of the output sequence $y_1, \ldots, y_n$ conditioned on the input sequence $x_1, \ldots, x_m$. It uses two separate *recurrent networks*[3]. The first, called the Encoder, processes the input sequence. Its last hidden state represents a fixed-dimensional representation r of the input. r is then used to initialize the hidden state of the second recurrent network, called the Decoder, which models the conditional probability of the output sequence (equation 3.9).

$$p(y_1, \ldots, y_n | x_1, \ldots, x_m) = \prod_{t=1}^{n} p(y_t | r, y_1, \ldots, y_{t-1}) \tag{3.9}$$

The dimensionality of the output of the Decoder at time-step t is the same as the size of the output vocabulary. The softmax (equation 3.10) over the outputs is used to represent the distribution $p(y_t | r, y_1, \ldots, y_{t-1})$.

$$softmax(\boldsymbol{x})_i = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}} \tag{3.10}$$

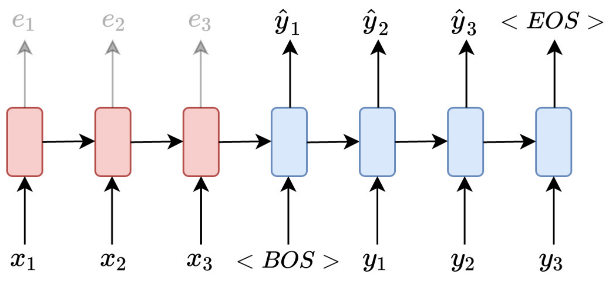
Training

The Decoder is trained under the *teacher-forcing* regime. The main gist of this approach is to feed the gold output y_{t-1} as the input at time-step t. Since there

[3]Here we refer to *recurrent network* as to a complex consisting of at least one RNN/LSTM/GRU/... rather than to a single recurrent layer.

is no zeroth gold output we use a special $<BOS>$ (*beginning of sequence*) token as the first input to the Decoder.

Another special token, the $<EOS>$ (*end of sequence*) token is appended at the end of each target sequence. This way we train the model to explicitly show when the generation is over (therefore the produced sequences can be of variable length). The visualization of the approach is shown in figure 3.3.



Note: Encoder is red, Decoder is blue
none of the Encoder's outputs is used

Figure 3.3: Visualization of the training of the Encoder-Decoder Architecture with *teacher forcing*.

Inference

In the inference phase, we want to find a sequence of tokens $y_1, \dots, y_n$ which maximizes the probability

$$p_{model}(\boldsymbol{y}|\boldsymbol{x}) = p_{model}(y_1|\boldsymbol{x})p_{model}(y_2|y_1,\boldsymbol{x})\dots p_{model}(y_N|y_1,\dots,y_{N-1},\boldsymbol{x}) \tag{3.11}$$
$$= \prod_{t=1}^{N} p_{model}(y_t|y_1,\dots,y_{t-1},\boldsymbol{x}) \tag{3.12}$$

Calculating all $\mathcal{O}(N^{|V|})$ sequences and choosing the maximal is surely the most accurate option, although computationaly infeasible. Therefore we only approximate the optimal solution.

Greedy Decoding

Greedy Decoding provides the simplest approximation of the optimal sequence. At each time-step we take the most probable token under the model distribution as the output. The process ends when the $<EOS>$ token is generated.

$$\hat{y}_1 = \arg\max_{y'} p_{model}(y'|\boldsymbol{x})$$
$$\hat{y}_2 = \arg\max_{y'} p_{model}(y'|\hat{y}_1,\boldsymbol{x})$$
$$\dots$$
$$<EOS> = \arg\max_{y'} p_{model}(y'|\hat{y}_1,\dots,\hat{y}_{n'},\boldsymbol{x})$$

The suboptimality of the algorithm can be seen on a simple example. E.g. let's say that we have a training corpus consisting of sentences describing the eating habits of the author of this text. The corpus consists of sentences ”I eat a banana”, ”I eat a peach”, ”I eat a goulash” and two repetitions of sentence ”I eat an apple”. Starting from the state after generating subsequence ”I eat”, the greedy decoder would pick “a” as the most probable continuation of the sequence. However the optimal solution would pick ”an”, because none of the possible continuations of subsequence ”I eat a” is as probable as ”I eat an apple” which is the most occuring sentence in the corpus.

Beam Search Decoding

Beam Search builds on the greedy decoding approach. We keep track of k most promising *hypotheses* (and associated hidden states). A hypothesis is a sequence of generated tokens $y_1, \dots, y_{n'}$. We compute its score (equation 3.13).

$$score(y_1, \dots, y_{n'}) = \sum_{i=1}^{n'} \log p_{model}(y_i | y_1, \dots, y_{i-1}, \boldsymbol{x}) \tag{3.13}$$

At each time-step we expand all the hypotheses (take k most probable tokens under the respective hypothesis, which will result in k^2 possibilities), and choose k with the highest score. k is called the *beam size*. An example of the approach can be seen in figure 3.4. There exist several options what to do when some hypothesis expands to $<EOS>$ token. The finished hypothesis can be put aside and the generation continues until T-th time-step (T is another hyperparameter of the algorithm), or until at least N hypotheses are finished. We choose yet another option, to end the generation right after the first $<EOS>$ is generated[4].

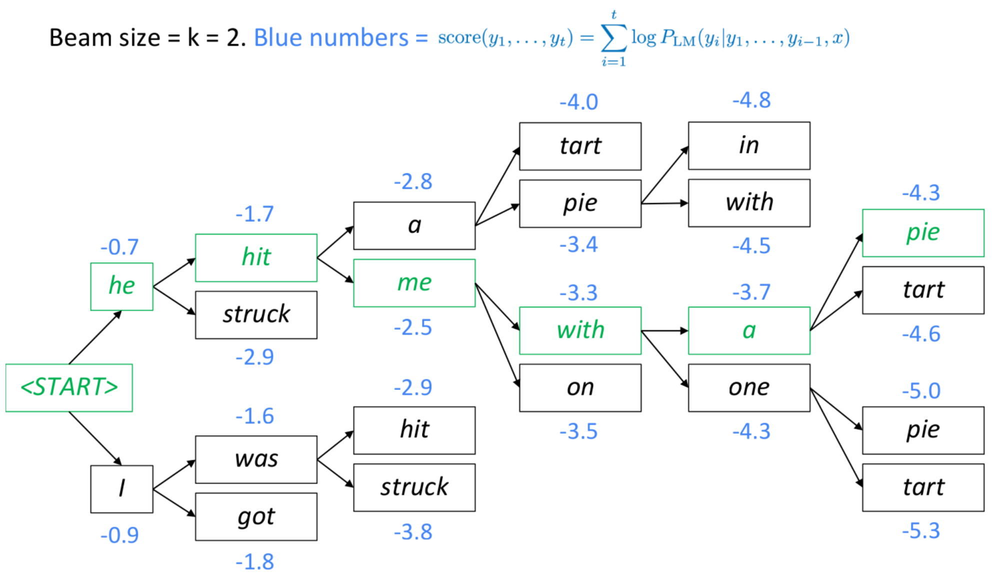


Figure 3.4: Beam-Search decoding, excerpt from the slides to lecture about Machine Translation, Seq2Seq and Attention on Stanford `http://web.stanford.edu/class/cs224n/`

[4]This option may suffer from generating too short summaries (because some hypothesis at the beginning may expand to $<EOS>$ token and beat all the remaining ones although they may have had better score), however we have not experienced this problem.

3.1.4 Problems of the Encoder-Decoder Architecture

Despite having many advantages (variable length of the input and output sequence, possibility of extending the number of recurrent layers in the encoder and the decoder) there are some major flaws that need to be overcome in order to generate text from structured data.

Fixed-dimensional Representation of the Input Sequence

It has been shown by Cho et al. [2014a] that the performance of the Encoder-Decoder architecture ”suffers significantly from the length of sentences”. Bahdanau et al. [2014] hypothesize that it may be because all of the information from the source sequence is encoded to the fixed-dimensional vector. Both mentioned papers understand word *”long”* as *longer than 30 tokens*. From the chapter about the preprocessing 2, we know that there are more than 300 records in the average input from the RotoWire dataset. Consequently this particular problem should be seen in our task.

Rare-word Problem and Hallucinations

In the standard Encoder-Decoder, the output is a distribution over the output vocabulary. At the start of the training each word is equally probable in any given context (assuming reasonable weights initialization). During training, model learns the language model on the training data. There are several flaws in the design:

1. It essentially means that e.g. words ’the’ and ’Roberta’ compete against each other, although one depends purely on the language skill (perhaps the next token after ’the’ would be superlative) and the other one on the input sequence (which probably mentions some AI research).

2. As pointed out by e.g. Gulcehre et al. [2016], (although not on this particular example) word ’Roberta’ occurs less frequently in the training data than the word ’the’, thus it is ”difficult to learn a good representation of the word, which results in poor performance”[5]

3. Networks tend to *hallucinate* the facts. E.g. from the record {*type:transformer; value:GPT*} network generates a sentence ”The famous example of transformer architecture is BERT.” To put it simply, the network knows it should talk mention a transformer, therefore each word describing some kind of a transformer is somewhat probable, even if it wasn’t seen in the actual input.

We have already discussed how to increase the average frequency of a token to minimize the Rare-Word Problem through preprocessing (section 2.6). In the following sections we show the methods that handle hallucinations (section 3.3).

[5]The problem is called *The Rare-Word Problem.*

3.2 Attention Mechanism

The Attention mechanism should cope with the issue of fixed-dimensional representation of the input sequence 3.1.4. As stated by Bahdanau et al. [2014] "The most important distinguishing feature of this approach from the basic encoder-decoder is that it does not attempt to encode a whole input sequence into a single fixed-length vector".

The encoder is a recurrent neural network[6]. From the overall architecture (figure 3.3) we can see that only the last hidden state of the encoder is used, although there are encoder outputs for each time-step. Bahdanau et al. [2014] propose an architecture which takes advantage of this simple observation. In our work we use a little refinement, proposed by Luong et al. [2015].[7]

3.2.1 Computation

Let's start with the description of the computation that produces the attention output.

As stated previously, the Encoder encodes the input sequence to *encoder outputs* $\boldsymbol{e} = (e_1, \ldots, e_m)$ and the Decoder RNN is initialized with the last hidden state of the Encoder.

Let d_t be the output of the Decoder RNN at t-th time-step. At first we calculate the *score vector* $\boldsymbol{s_t} = (s_{t,1}, \ldots, s_{t,m})$. Its elements are computed using *a score function* (which we will talk about below 3.2.2):

$$s_{t,i} = score(e_i, d_t) \tag{3.14}$$

According to Bahdanau et al. [2014], the alignment vector $\boldsymbol{a_t}$

$$\boldsymbol{a_t} = softmax(\boldsymbol{s_t}) \tag{3.15}$$

"scores how well the inputs around position i and the output at position t match". The weighted sum of the outputs of the encoder, is called a *context vector* for time-step t.

$$c_t = \sum_{i=1}^{m} a_{t,i} e_i \tag{3.16}$$

Unlike in the standard Encoder-Decoder architecture, the output of the decoder also depends on the context vector.

$$att_t = tanh(W_c[c_t; d_t]) \tag{3.17}$$

$$p(y_t | y_{<t}, x) = softmax(W_y att_t) \tag{3.18}$$

3.2.2 Score Functions and Input Feeding

Luong et al. [2015] experimented with three different types of score functions. We adopted two of them, the *dot* and *concat* ones. (The following equations are

[6]From now on, I'll stick to refer to *recurrent neural network* as to the neural network consisting of at least one *tf.keras.layers.RNN* or relatives.

[7]Since we do not experiment with the original Bahdanau attention, we only show the Luong's approach. Luong et al. [2015] show all the differences between his and Bahdanau's approach in section 3.1 of the paper.

directly extracted from the Luong's paper)

$$score(e_i, d_t) = \begin{cases} e_i^\top d_t & dot \\ v_s^\top tanh(W_s[e_i; d_t]) & concat \end{cases}$$

The same author also states that the fact that the attentional decisions are made independently is *suboptimal.* Hence the *Input Feeding* approach is proposed to allow the model to take into acount its previous decisions. It simply means that the next input is the concatenation $[y_t, att_t]$ (as shown in figure 3.5).

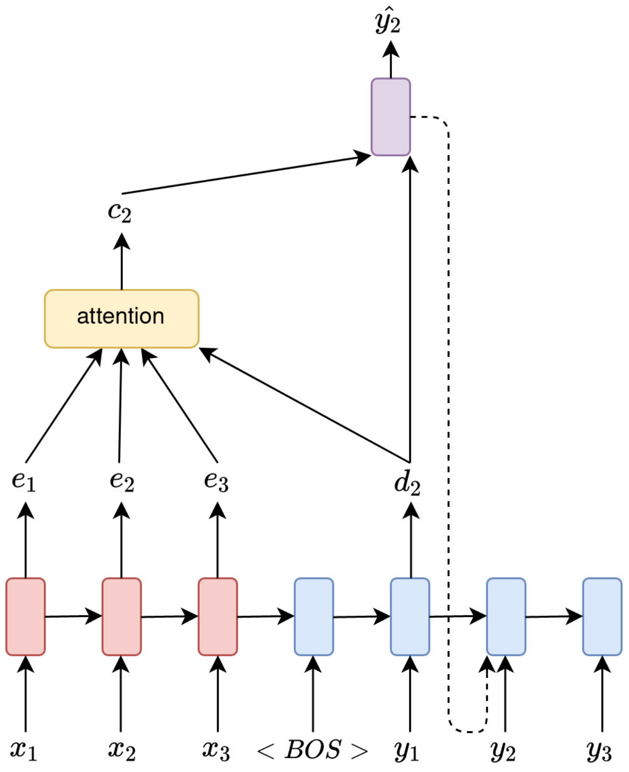


Figure 3.5: The Attention mechanism at the second time-step. Dotted line represents the input feeding approach.

3.3 Copy mechanism

The copy mechanism is a further extension of the attention mechanism. In this section we discuss the Pointer networks [Vinyals et al., 2015], which are trained to *point* to some position in the input sequence and the Copy Mechanisms [Gulcehre et al., 2016], [Gu et al., 2016], [Yang et al., 2016] which model the decision making (whether to copy from the pointed location or to generate from the actual context).

3.3.1 Pointer Networks

The Pointer networks [Vinyals et al., 2015] leverage the fact that the alignment vector $\boldsymbol{a_t}$ can be seen as *a pointer* to the input sequence. Consequently instead of computing the weighted sum (*context vector*) and an MLP on top of that as the Attention models, they utilize the *alignment vector* as an output.

3.3.2 Approaches to Copying

Gulcehre et al. [2016] note that the ability to point is useless in the generation task if the network is always forced to point. Therefore they introduce a new switching network that outputs a binary variable z_t , which models the probability of the required action being pointing or generating.

Let $\boldsymbol{e} = (e_1, \ldots, e_m)$ be the encoder outputs, $\boldsymbol{x} = (x_1, \ldots, x_m)$ the input sequence, d_t the output of the Decoder RNN at the actual time-step, and $ATTN$ the Attention as presented in the previous section.

The probability of gold output y_t and gold switch decision z_t is decomposed to $p^{gen}(y_t|\boldsymbol{x})$ (the probability that y_t should be generated), $p^{switch}(z_t|\boldsymbol{x})$ (the probability that we should copy) and $p^{copy\_pos}(y_t = x_i|\boldsymbol{x})$ (the probability that y_t should be copied from the input position i).:

$$\boldsymbol{a_t} = ATTN(\boldsymbol{e}, d_t) \tag{3.19}$$

$$p^{copy\_pos}(y_t = x_i|\boldsymbol{x}) = a_{t,i} \tag{3.20}$$

$$\boldsymbol{c_t} = \sum_{i=1}^{m} e_i * a_{t,i} \tag{3.21}$$

$$p^{switch}(z_t|\boldsymbol{s}) = sigmoid(W_{switch}[\boldsymbol{c_t}, d_t]) \tag{3.22}$$

$$p^{gen}(y_t|\boldsymbol{s}) = softmax(W_{gen}[\boldsymbol{c_t}, d_t]) \tag{3.23}$$

Gulcehre et al. [2016] explicitly model each of these probabilities (therefore the targets contain 3 values for each time-step). Yang et al. [2016] marginalize out the switch probability z_t, and they model $p = p^{copy} * p^{switch} + p^{gen} * (1 - p^{switch})$.

To be able to follow their path, we take the one-hot encoding of each input and compute the weighted sum:

$$p^{copy}(y_t|\boldsymbol{x}) = \sum_{i=1}^{m} p^{copy\_pos}(y_t = x_i|\boldsymbol{x}) * x_i \tag{3.24}$$

Throughout our task the input and output vocabularies are shared, therefore the weighted sum of the inputs has the same dimensionality as the output generation distribution p^{gen}.

Consequently, the probability of the gold output y_t at time-step t is computed as follows:

$$p(y_t|\boldsymbol{x}) = p^{gen}(y_t|\boldsymbol{x}) * (1 - p^{switch}(1|\boldsymbol{x})) + p^{copy}(y_t|\boldsymbol{x}) * p^{switch}(1|\boldsymbol{x}) \tag{3.25}$$

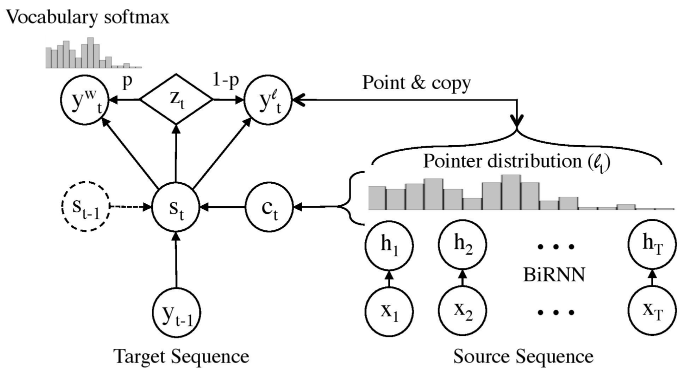


Figure 3.6: Excerpt from **Pointing the Unknown Words** paper by Gulcehre et al. [2016], showing how the attention alignment can be utilized as a pointer information

4. Experimental Setup

In this chapter we aim to clarify how we set up the neural network models for the experiments (which will be discussed in the next chapter 5). At first we present a *baseline model.* Model, which is sufficiently competitive to be able to generate reasonable texts. Then we present changes to the architecture, which aim to improve the generation.

We follow the path set up by Wiseman et al. [2017]. We begin with purely end-to-end approach (Encoder-Decoder with attention). Next we try to improve the Decoder with the copy mechanism 3.3. Inspired by Puduppully et al. [2019], we continue by enhancing the Encoder with Content Selection mechanism, and dividing the task to *content planning* and *text generation.*

4.1 Truncated Backpropagation Through Time

It was really challenging to set up even the baseline model. Since the input sequences are about 600 records long and output sequences are more than 300 tokens in average (and the outputs are padded with <*PAD*> token to approximately 800 tokens), it wasn't possible to fit the model into the GPU memory. (The GPUs at `https://aic.ufal.mff.cuni.cz` have about 8GBs of memory[1])

Computing and updating gradient for each time-step of a sequence of 800 tokens has approximately the same cost as forward and backward pass in a feed-forward network that has 800 layers. Williams and Peng [1998] propose a less expensive method. Truncated Backpropagation Through Time (TBPTT) processes one time-step at a time, and every t_1 timesteps it runs BPTT for t_2 timesteps.

To illustrate our implementation of the algorithm, we show how we process an output sequence which is longer than 150 tokens. Let $t_1 = 50$, $t_2 = 100$. At first we let the network predict the first 100 outputs and run the BPTT. We keep aside the 50-th hidden state of the decoder. Next the network (initialized with the hidden state from the 50-th time-step) predicts positions 51 to 150, and again the BPTT is run. Similarly afterwards.

4.2 Baseline model

We use a non-recurrent Encoder and a two-layer LSTM decoder with Luong-style attention as the baseline model. At first we present how the encoding of input records works, then we discuss the text generation. We highlight all the differences between our approach and the one taken by Wiseman et al. [2017]. The visualization of the model is shown in the figure 4.1.

4.2.1 Encoder

The Encoder should process the input records (the formation of a record is explained in section 2.3.3) to create the partial outputs at each time-step and the initial hidden state for the Decoder.

[1]The exact GPU used on AIC cluster is NVIDIA GeForce GTX 1080

We described in section 2.3.5 that each record r consists of 4 different features: *type*, *value*, *entity* and a *home/away flag* depicting if the record belongs to home or away team.

First, each feature is embedded to a fixed-dimensional space. Next, the embeddings are concatenated. We choose the same approach as Wiseman et al. [2017] (who was inspired by Yang et al. [2016]), and we pass the concatenation through a one layer feed-forward network (*tf.keras.layers.Dense*) with ReLU activation[2], to create the encoding e of the record r. Consequently, the input sequence of records $\{r_i\}_{i=1}^m$ is transformed to $\boldsymbol{e} = \{e_i\}_{i=1}^m$.

To create the initial state of the decoder, Wiseman et al. [2017] calculated the mean of the records belonging to the particular entity and linearly transformed the concatenation of the means. (the concatenation is passed through *tf.keras.layers.Dense* without any activation function).

To make the implementation simpler we observe that each player entity is represented by 22 records and each team entity by 15 records 2.3.3. Consequently we approximate the approach taken by Wiseman et al. [2017] and mean pool over $\boldsymbol{e}$ with stride 22. During our experiments we haven't seen any indication that this modification became the performance bottleneck of the model.

4.2.2 Decoder

The Decoder is a 2-layer LSTM network with attention mechanism. The LSTMs are initialized with states prepared in the previous section. We opted to use the Luong style attention with input feeding [Luong et al., 2015]. We described in section 3.2.2 that we use the concatenation of the last attentional decision and the last gold output as the actual input to the first layer of LSTMs. However at the first time-step, when the input is the <*BOS*> token, there is no *last attentional decision*. Hence for this purpose we use one of the initial states prepared by the Encoder.

4.2.3 Training

Given an input table $\boldsymbol{x}$ and the corresponding gold output summary $\boldsymbol{y}$ the model approximates the conditional probability of the latter conditioned on the former $p(\boldsymbol{y}|\boldsymbol{x})$. Following the maximum likelihood principle (e.g. section 5.5 in [Goodfellow et al., 2016]) the model is trained by minimizing the cross-entropy loss (negative log likelihood) on the training set $\mathcal{D}$.(equation 4.1).

$$-\sum_{(\boldsymbol{x},\boldsymbol{y})\in\mathcal{D}} log\ p_{model}(\boldsymbol{y}|\boldsymbol{x}) \tag{4.1}$$

As explained in section 3.1.3 the training happens under *teacher-forcing* setting. The minimization is provided by stochastic gradient descent, specifically we opted to use one of the standard algorithms, Adam [Kingma and Ba, 2014]. Since this algorithm associates specific learning rate to each of the trainable network parameters, we modify only the initial learning rate parameter[3].

[2]the Rectified Linear Unit activation function $f(x) = max(0, x)$

[3]It means that we do not try e.g. learning rate decay.

We report the loss value as well as the accuracy[4] of the model on the training set, to be able to detect *underfitting* (this happens when a model is unable to achieve sufficiently low loss value on the training part of the dataset).

The main challenge is to obtain good results on previously unseen data. Therefore we report the loss value, and the accuracy of the model on the validation part of the dataset (also collected under *teacher-forcing* setting). We consider the model with the lowest loss value and accuracy on the validation set to be the best[5].

4.2.4 Regularization

Two regularization methods are used, Dropout and Scheduled Sampling.

"The key idea of Dropout is to randomly drop units (along with their connections) from the neural network during training." [Srivastava et al., 2014]. A unit is dropped with probability p that can be set as a hyperparameter. (e.g. $p = 0$ would mean no dropout) We apply the dropout on the outputs of the LSTM cells.

The Scheduled Sampling aims to minimize the difference between training and inference. Bengio et al. [2015] note that using any of the two generation techniques described in sections 3.1.3, 3.1.3 the model can get to the "state space that is very different from those visited from the training distribution and for which it doesn't know what to do". They propose to "bridge the gap" by feeding either gold y_{t-1} or the prediction of the model $\hat{y}_{t-1}$ as the input at t-th time-step. The decision whether to use gold is made independently for each input with probability p' which is another hyperparameter of the training. They propose to decay p' over time with similar strategies as used with learning rate.

4.3 Improving the Baseline with Copy Mechanisms

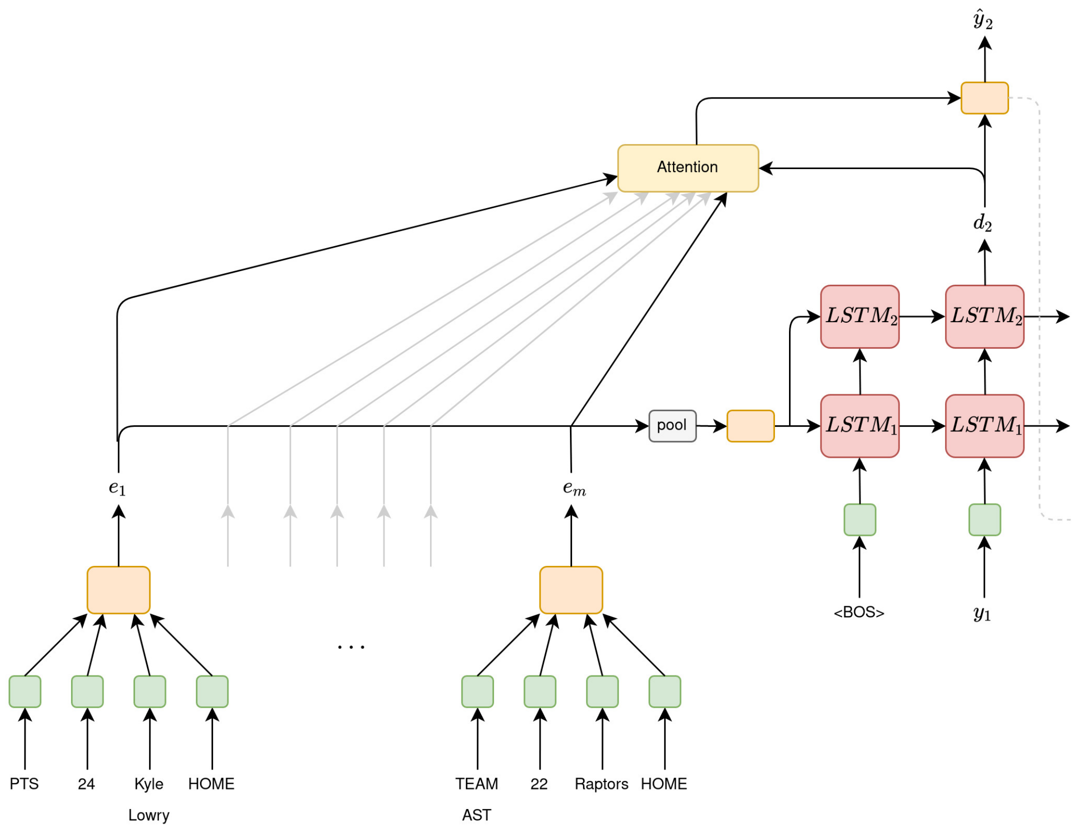
In section 3.1.4 we underlined *hallucinations* as one of the problems of the Encoder-Decoder architecture. In the task on RotoWire dataset it basically means that during training, the model learns that it should put *some number* at a specific place in the sentence. We would like it to generate the *exact value.*

Therefore as the next step we incorporate the *Joint Copy mechanism* [Gu et al., 2016], [Yang et al., 2016] (already described in 3.3). The encoder rests intact, however in the decoder we use another attention module to point to specific record from the input table and a feed-forward network which models if the model should generate or copy. In the following chapter we call this kind of model *Copy* model.

The generational path is the same as in the baseline model. In the copy path we use the alignment vector from the newly added attention as weights to compute the weighted sum of the value portion of input records. The visualization can be seen in the figure 4.2.

[4]the frequency with which the most probable token in the distribution generated by the model matches the gold token

[5]We also report the BLEU score [Papineni et al., 2002] of the text generated from a subset of the validation dataset. Frequently, there are multiple epochs where the model achieved similar performance. We pick the one which generated the best text according to BLEU.



Note: green cells are embedding layers, orange cells are feed-forward networks

Figure 4.1: The Rotowire baseline model at the second time-step.

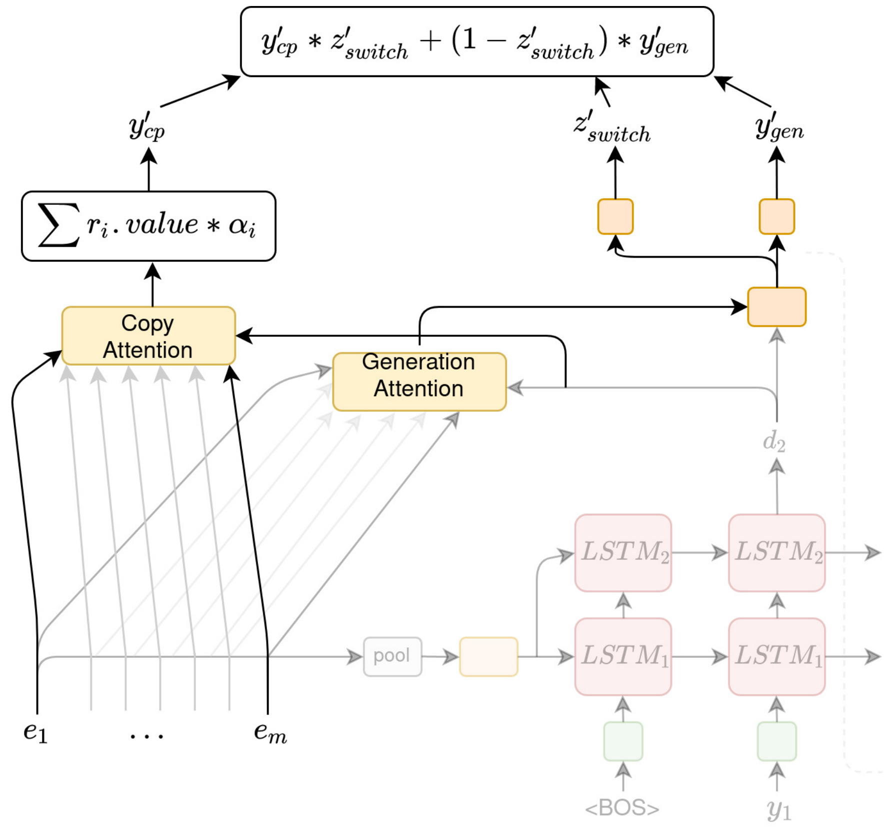
4.4 Content Selection and Planning

Rather than training end-to-end, [Puduppully et al., 2019] suggest to divide the task to *content planning* and *text generation*. The *content plan* describes ”what to say, and in what order”. During the *content planning* stage the model selects some records from the input table and organizes them to a *content plan*. During the *text generation* stage, the model generates the text based on the records pointed to by the *content plan*.

Both tasks are modelled with *the same* Encoder and with *separate* Decoders.

4.4.1 Content Selection

[Puduppully et al., 2019] improves the baseline encoder by incorporating *context awareness*. At first the input records are encoded in the same way as in the baseline model 4.2, the self-attention is used to model the ”importance vis-a-vis other records in the table”.



Note: green cells are embedding layers, orange cells are feed-forward networks α is the alignment vector produced by the copy attention; $r_i.value$ is the value portion of the i-th input record.

Figure 4.2: The Joint-Copy extension of the baseline model at second time-step.

Specifically, we compute

$$
\begin{aligned}
\forall k \neq t : \alpha_{t,k} &= score(r_t, r_k) && \textit{the score vector} \\
\boldsymbol{\beta_t} &= softmax(\boldsymbol{\alpha_t}) && \textit{the alignment vector} \\
\boldsymbol{\gamma_t} &= \sum_{i=1}^{m} \beta_{t,i} * r_i && \textit{the context vector} \\
r_t^{att} &= W_{cs}[r_t, \boldsymbol{\gamma_t}] \\
r_t^{cs} &= sigmoid(r_t^{att}) \odot r_t && \textit{the content selected representation}
\end{aligned}
$$

The Content Selection Encoder thus creates a sequence of *context aware* representations $\{r_t^{cs}\}_{t=1}^{m}$ (figure 4.3). We experiment with a model using Content Selection Encoder and Joint-Copy decoder (we call it *CopyCS*).

4.4.2 Content Planning

Wiseman et al. [2017] experimented with conditional copy approach, in which the latent *switch* probability isn't marginalized out. Hence, there exists pointer sequence for each summary in the train and validation dataset. The sequence corresponds to the order in which entities and values from the sequence of input records appear in the output summary. Puduppully et al. [2019] suggested that

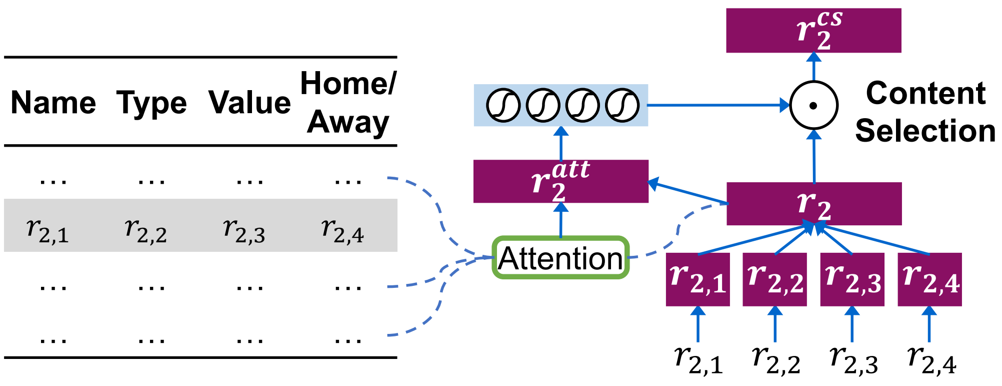


Figure 4.3: Content Selection mechanism (image is directly from [Puduppully et al., 2019])

instead of just modelling the switch probability, we can train a Decoder to extract these pointers from the original table.

As suggested, the Content Planning Decoder is a one layer LSTM which operates on the *context aware* representations $\boldsymbol{r}^{cs}$. Its hidden states are initialized with $avg(\{r_t^{cs}\}_{t=1}^{m})$. Puduppully et al. [2019] have not elaborated on the exact approach, hence it is probable that we have diverged a little bit from the intentions of original authors.

Type	**Entity**	**Value**	**H/A flag**
<<BOS>>	<<BOS>>	<<BOS>>	<<BOS>>
TEAM-CITY	Raptors	Toronto	HOME
TEAM-NAME	Raptors	Raptors	HOME
TEAM-PTS	Raptors	122	HOME
TEAM-CITY	76ers	Philadelphia	AWAY
TEAM-NAME	76ers	76ers	AWAY
TEAM-NAME	76ers	76ers	AWAY
TEAM-PTS	76ers	95	AWAY
...	...	...	...

Note: The extract corresponds to sentence: "The host Toronto Raptors defeated the Philadelphia 76ers , 122 - 95..."

Table 4.1: An extract from the content plan corresponding to the summary from the figure 1.1

The Text Decoder is trained to start the generation when it sees the <*BOS*> token. Since the Content Planning Decoder operates on $\boldsymbol{r}^{cs}$ we have chosen to prepend a special <*BOS*> record to the sequence of input records, and also a pointer to the <*BOS*> record is prepended to each content plan. Therefore instead of teaching the Content Planning Decoder to start generating content plan when seeing a special value, we teach it to do so when seeing *the encoded representation of the special value.* The same approach is taken at the end, with the <*EOS*> record.

Puduppully et al. [2019] use a one layer bidirectional LSTM on top of the generated content plans as shown in figure 4.4 (in the following text we call this part of the model *Content Plan Encoder*).

Joint-Copy Decoder operates as the Text Decoder to generate the output summary. In the following chapter we experiment with two models inspired by this approach. Firstly, we train Content Selection and Planning model as visualized in figure 4.4 (the model is called *CS&P*). Secondly, we simplify the input tables and train the exact same model without the Content Planning Decoder (the model is called *CopyCSBidir*).

4.4.3 Training and Inference

At first let me elaborate on the training of *CS&P*. The model consists of two parts which are trained jointly. According to notation in figure 4.4 the model has two sets of outputs for which we calculate the content planning loss and the text decoding loss. These are added together to form the overall loss which is minimized by the optimizer. During training the inputs to the Content Plan Encoder are the encoded records pointed by the *gold content plan*. Equation 4.2 shows the loss value we aim to minimize during training, given the input sequences $\boldsymbol{x}$, gold content plans $\boldsymbol{z}$ and gold summaries $\boldsymbol{y}$.

$$\sum_{(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})\in\mathcal{D}} -\log p(\boldsymbol{y}|\boldsymbol{z},\boldsymbol{x}) - \log p(\boldsymbol{z}|\boldsymbol{x}) \tag{4.2}$$

There are many possibilities what to do during inference. In section 5.5 we mention five options. The outputs of the Content Planning Decoder can be obtained using Greedy or Beam Search decoding, similarly for the Text Decoder. At last there is possibility to ignore the Content Planning Decoder and use the encoded records pointed to by the gold content plan. (if we have any gold content plan available). Equation 4.3 shows the quantity we aim to minimize during the inference.

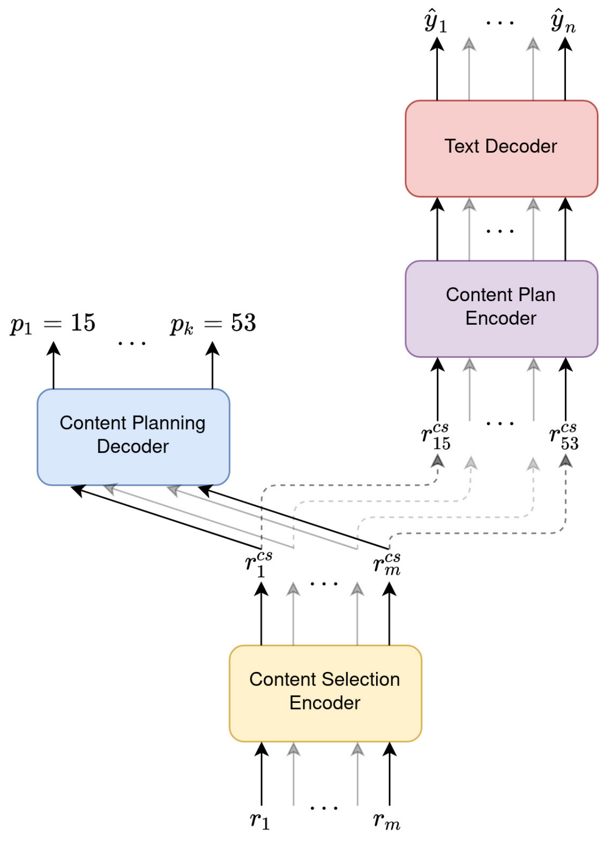
$$\arg\min_{\boldsymbol{y'},\boldsymbol{z'}} \log p(\boldsymbol{y'}|\boldsymbol{z'},\boldsymbol{x}) + \log p(\boldsymbol{z'}|\boldsymbol{x}) \tag{4.3}$$

4.5 Postprocessing

The models are trained to generate lowercased Byte Pair Encoded sequences. During the postprocessing we merge the tokens belonging to one word together (e.g. *"contribu⋆ tor"* → *"contributor"*), split the tokens of named entities (e.g. *"LeBron_James"* → *"LeBron James"*) and uppercase the first letter of a sentence (using NLTK[6] library we split the summaries to sequences). Since the vast majority of unique tokens (more than 98.6%) from the validation and test sets (section 2.8) is in the vocabulary collected from the training set, we opted to ommit resolution of *UNK* tokens[7].

[6]`https://www.nltk.org/`

[7]If we were forced to resolve the *UNK* tokens, we would take the simplest possible approach. We would look at the last alignment produced by Copy Attention mechanism and copy the tabular value which is considered to be the most important according to the alignment.



Note: $p_1 = 15$ means that the first generated pointer points to 15-th encoded record (therefore r^{cs}_{15} the first input to the Content Plan Encoder), similarly for p_k

Figure 4.4: Overall architecture of the Content Selection and Planning model with example outputs.

5. Experiments

In previous chapters we have presented the dataset (chapter 1), and discussed challenges which arise from its properties (chapter 2). Next, we described the neural network architectures (chapter 3) which served as building blocks for the models introduced in chapter 4. Now we want to connect all parts together, elaborate on the evaluation methods and analyze the results of different models.

Let us recap the main challenges we face, and hypothesize about the ideal generation system. Firstly, the target summaries are really long. The ideal system should remember what has already been generated and shouldn't produce duplications. Secondly, the targets contain a lot of facts based on the input structured data. The ideal system should copy these facts from the input and reduce *hallucinations.* Lastly, the generated text should be as close to English as possible *while meeting the requirements described previously.*

5.1 Evaluation Methods

During evaluation we want to measure which model resembles the hypothetical ideal model the most. To do so, we report the BLEU score [Papineni et al., 2002] of the postprocessed generated summaries on the validation and test sets. Although it is the gold standard, there are many people arguing against its usage as a performance metric [Celikyilmaz et al., 2021]. Since the BLEU score does not explicitly penalize hallucinated statements, or reward the right selection of entities to talk about, we also manually evaluate a subset of the generated summaries.

5.1.1 Manual Evaluation

We used a pseudo random generator to pick 8 different data points, 4 from the validation and 4 from test set[1]. We looked at the factual correctness (how many of the generated numbers describing team and player statistics are based on the input tabular data), and entity recall (how many of the entities mentioned in the gold summaries are present in the generated ones). Due to time-requirements of the process, only the best model[2] is manually evaluated. Therefore manual evaluation should show the differences between approaches and architectures rather than between variations of the same model.

5.1.2 Ommited Evaluation Methods

Wiseman et al. [2017] proposed three custom automated metrics to evaluate the performance of their models. They call them *Content Selection* ("how well the generated document matches the gold document in terms of selecting which records to generate"), *Relation Generation* ("how well the system is able to generate text containing factual (i.e., correct) records") and *Content Ordering* ("how

[1]Specifically samples 132, 319, 475 and 709 from the validation set and samples 16, 247, 585 and 671 from the test set

[2]In the respective sections we explain why we think the selected model is the best one.

well the system orders the records it chooses to discuss”). The metrics are implemented in the outdated neural network framework *Torch* and we were not able to execute it on my computers. After discussions with my advisor we agreed to not adopt these methods.

5.1.3 Comparison to Related Work

Due to massive preprocessing we have introduced, our results are not directly comparable to any related work. (E.g. the name transformations introduced in section 2.4.2 and lowercasing increase the BLEU score, while being practically irreversible[3])

5.2 Baseline Model

At first we would like to summarize our expectations. Wiseman et al. [2017] note that even models with explicit copy mechanisms tend to *hallucinate* the facts. However they do not show the results of any baseline without copying. We expect the baseline to generate a fairly good English, even though the summaries should not be factually correct.

We searched through the hyperparameter space (possible combinations of learning rates, dropout probability p, hidden state dimensionality etc.) until the generated language as well as the numerical results haven’t fulfilled the expectations at least by half.

The overall architecture of the baseline model is discussed in section 4.2. Figure 5.1 shows the hyperparameter choice for discussed baseline models.

Hidden States Dimensionality	**Learning Rate**	**Batch Size**
600	0.001	16

Token	**Embedding Dimensionality**
record.type	300
record.home_away	300
record.value	600
record.entity	600
summary token	600

Figure 5.1: Hyperparameter settings for baseline models.

The first baseline model is trained without any regularization[4], the second one with dropout on the output LSTM units with $p_{dropout} = 0.3$ (the probability that the unit is dropped is 0.3) and scheduled sampling with constant rate of 0.8 (the probability that the gold output from the previous timestep is used as the actual input is 0.8). We discussed two possibile implementations of the score function in the Attention mechanism in section 3.2.2. In our experiments we have not seen any difference in performance of the methods, thus in the following text we always use the *dot* score function.

[3]It is impossible to tell if the player should be called by his full name or only by his second name.

[4]We trained the model just to see how far we can get without any advanced methods.

5.2.1 Results

Baseline model wasn't able to capture the relationships between the input tabular data and the output summaries (the best configuration achieved perplexity 10.59). We found that dropout helps to reduce overfitting while scheduled sampling improved the quality of the generated summaries. (We present only models that achieved reasonable performance.) The quality of generated summaries is further improved with beam search. Although the statement contradicts the calculated BLEU scores (as the score decreased after introducing beam search), the summaries contain more natural language and less repetitions. The expectations are fulfilled in terms of *hallucinations*, as the model makes up *almost all the factual statements.*

Model	Validation Perplexity	Validation BLEU	Test BLEU	Entity Recall	Factual Correctness
BN_G	12.68	9.04	9.10	–	–
BN_{B5}		8.73	8.55	–	–
BR_G	10.59	10.0	10.47	–	–
BR_{B5}		9.99	10.6	37.35%	8.03%

$_G$ - Greedy Decoding

$_{B5}$ - Beam search decoding, beam size = 5

BN - Baseline, non-regularized

BR - Baseline, regularized (dropout 0.3, scheduled sampling 0.8)

Table 5.1: Performance metrics on the baseline models.

Figure 5.2 shows an example generated by the regularized baseline model with beam search decoding. We observe[5] that the score, the winning-loosing records[6] as well as all the individual statistics are *hallucinated.* We found that the model repeatedly (over multiple observed summaries) mentions the same players and uses the same numbers. This experiment thus supports our assumptions. Statistics in table 5.1 show that only about 8 % of the numbers aren't *hallucinated* and that the recall is lower than 38 %. Therefore we can conclude that model learned to produce probable numbers and names of star players of the respective teams.

5.3 Joint-Copy Model

The Joint-Copy Model is expected to produce more factually correct statements. Wiseman et al. [2017] select this model as their baseline. We would like to reiterate that due to massive preprocessing that we introduced, the results we obtained aren't comparable to theirs. (E.g. Wiseman et al. report BLEU 10.41 for the Joint-Copy model while we obtained similar scores with *simpler baseline model.*)

The additional complexity of the model increases the memory demands. Therefore we use lower dimensional embeddings, hidden states and smaller batch size

[5]We opted to not show the same tabular information multiple times. A part of the table corresponding to the generated summary can be found in figure 1.1

[6] *"The Raptors (21 - 15)"* means that Raptors have won 21 matches and lost 15 matches this season.

The Toronto Raptors defeated the Philadelphia 76ers , 109 - 95 , at air canada centre on tuesday . The Raptors (21 - 15) checked in to saturday 's contest trying campaign , having won 7 of their last 7 games . However , Philadelphia was able to pull away in the second half , as they outscored Philadelphia by a 59 - 44 margin over the second and third periods . DeMar DeRozan led the way with a points - point , 10 - rebound double - double that also included an assist , a steal and a block . Kyle Lowry was right behind with a points - point , 10 - rebound double - double that also included an assist , a steal and a block . Jonas Valanciunas posted a near double - double with 17 points , 9 rebounds , 2 assists and a steal . Jonas Valanciunas posted a near double - double with 11 points , 9 rebounds , 2 assists and a steal . Ersan Ilyasova was productive in a reserve role as well with 11 points , 4 rebounds , an assists and a steal . The Raptors head back home to take on the Toronto Raptors on saturday night , while the Raptors remain home to tangle with the Brooklyn Nets on tuesday evening as well .

Figure 5.2: A summary generated by the baseline model. The corresponding gold summary and input table is shown in figure 1.1.

to be able to train on the GPUs on the AIC. The hyperparameter settings are further discussed in figure 5.3. Compared to the baseline model we obtained the best results when training with 5-times lower learning rate.

Hidden States Dimensionality	**Learning Rate**	**Batch Size**
500	0.0002	8

Token	**Embedding Dimensionality**
record.type	300
record.home_away	300
record.value	500
record.entity	500
summary token	500

Figure 5.3: Hyperparameter settings for joint-copy models.

5.3.1 Results

We see the first major improvement in the BLEU score (more than 2 points) as well as in the manually evaluated metrics (almost 6-times better factual correctness). However the model fails in recognition of the structure of the table.

While it is able to copy facts, many times it copies statistics of wrong players (e.g. it learns that most of the time 5-th player from the input records is the most important one, therefore it mentions the 5-th player even if he scored unremarkable amount of points).

We also spotted that model learned that it is more probable that home team wins. Therefore it always produces sentence similar to *"The Denver Nuggets (11 - 17) defeated the Los Angeles Lakers (5 - 23) 111 - 107 on friday at the pepsi center in Denver . "* even if the score was reversed (*107 - 111* in favour of the Lakers).

Our observations of the generated summaries support the motivation for the Scheduled Sampling (section 4.2.4). The Copy model often generates a sequence of tokens so different from any in the training set that it gets lost in the generation. We can see numerous problems, e.g *cycling* (model generates one sentence multiple times), or unability to generate the <*EOS*> token which results in exceeding the maximal allowed length of a summary. (We don't allow the model to generate longer sequence than the longest one seen in the dataset (849 tokens)). Both phenomena can be seen in figure 5.4.

Contrary to observations on the baseline model neither greedy decoding nor beam search managed to significantly outperform the other method, and regularization methods did not provide any significant advantage over the unregularized case. (Therefore only results of unregularized models are presented.)

Model	**Validation Perplexity**	**Validation BLEU**	**Test BLEU**	**Entity Recall**	**Factual Correctness**
Copy$_G$	9.87	12.48	12.6	37.35%	47.29%
Copy$_{B5}$		12.19	12.5	39.76%	47.13%

Copy - Joint-Copy model

$_G$ - Greedy Decoding

$_{B5}$ - Beam search decoding, beam size = 5

After observations of the generated summaries we have chosen the Beam Search decoded ones for the manual evaluation.

Table 5.2: Performance metrics on Copy models.

The Toronto Raptors defeated the Philadelphia 76ers , 122 - 95 , at air canada centre on wednesday . The Raptors (11 - 14) were in the first quarter for the Raptors (4 - 14) , as the sixers (4 - 14) were able to pull away in the fourth quarter , out - scoring the 76ers 31 - 26 in the first quarter , while also holding the Raptors (4 - 14) by a 59 - 38 margin over the second and third quarters . However , the Raptors (11 - 14) shot 42 percent from the field and 68 percent from the three - point line , while the Raptors went 42 percent from the floor and 68 percent from the free - throw line . The Raptors also out - rebounded the Raptors 42 - 38 , while also holding the Raptors to just 42 percent . The Raptors were led by Joel Embiid , who finished with 24 points (7 - 14 fg , 6 - 6 ft) , 8 assists and 4 rebounds , in 32 minutes . Kyle Lowry was the only other starter to reach double figures , as he finished with 24 points (7 - 14 fg , 1 - 6 3pt , 4 - 5 ft) , 8 assists , 4 rebounds and 1 steal , in 32 minutes . Kyle Lowry was the only other starter to score in double figures , as he finished with 15 points (7 - 9 fg , 1 - 2 ft) , 5 rebounds and 8 assists , in 25 minutes . The other starter to reach double figures in scoring was DeMar DeRozan , who finished with 14 points (4 - 13 fg , 0 - 3 3pt , 6 - 6 ft) , along with 5 rebounds , 4 assists , 1 steal and 1 block , in 31 minutes . The other starter to reach double figures in scoring was DeMar DeRozan , who finished with 14 points (4 -

Figure 5.4: A summary generated by the joint-copy model. The corresponding gold summary and input table is shown in figure 1.1.

5.4 Content Selection Encoder with Joint-Copy Decoder

In section 4.4.1 we have built the *CopyCS* model. Puduppully et al. [2019] argue that Content Selection encoder contributes to improvement of the quality of the generated summaries. We expect the *CopyCS* model to resolve the problem of mixing statistical information of multiple players.

The hyperparameter configuration remains the same as in the Copy model (figure 5.3).

5.4.1 Results

The summaries produced by the model are richer in structure, as they mention more entities from the input tables (44.58 % vs 39.76 % for the Copy model). However we observe that many times model doesn't copy the players name (it only learns to copy numbers). E.g. it generates a sentence *"The Raptors were led by DeMar DeRozan , who finished with a team - high of 26 points (9 - 16 fg , 0 - 2 3pt , 8 - 9 ft) , to go along with 7 rebounds and 5 assists ."* where there would be 8/9 numbers correct if the name wasn't *DeMar DeRozan* but *Marc Gasol.* This causes the model to score less on the factual correctness metric (42.22 % vs 47.13 % for the Copy Model).

We hypothesize that it is due to marginalizing out the decision whether to copy or not. While every summary contains different numbers and model gets penalized for hallucinating them, it is often the case that star players are mentioned in each summary about a match where their team participated. Therefore model learns to mention the same players when describing a particular team.

Model	**Validation Perplexity**	**Validation BLEU**	**Test BLEU**	**Entity Recall**	**Factual Correctness**
CopyCS$_G$	9.93	13.53	13.62	–	–
CopyCS$_{B5}$		13.54	13.96	44.58%	42.22%

CopyCS - Joint-Copy decoder + Content Selection encoder

$_G$ - Greedy Decoding

$_{B5}$ - Beam search decoding, beam size = 5

Table 5.3: Performance metrics on the joint-copy model with content selection encoder.

Regarding BLEU score we see an improvement of about 1 point, however we would like to note that we don't think we came even close to the apex of the performance of this configuration. Many summaries still show indications of undertraining (e.g. sequences like *"TEAM-A defeated TEAM-A"*). We tried Scheduled Sampling, Dropout, different learning rates, different dimensionalities of the hidden layers, but we could not find the sweet spot. Therefore we do not show an example of the summary generated by the model (as it contains sentences of similar quality to the ones generated by the Copy model).

5.5 Content Selection and Planning

The biggest model we train is the *CS&P* model introduced in section 4.4. Multitude of added architectures (content selection attention, content planning attention, content planning LSTM) increased even more the memory demands. Therefore we again reduced the embedding and hidden state dimensionalities (figure 5.5).

Content Planning reduces the size of the table, and *arranges* the records into the same order in which they appear in the gold summary. There are two

Hidden States Dimensionality	**Learning Rate**	**Batch Size**
450	0.0002	8

Token	**Embedding Dimensionality**
record.type	300
record.home_away	300
record.value	450
record.entity	450
summary token	450

Figure 5.5: Hyperparameter settings for content selection and planning models.

aspects of this solution which should help the model to generate better summaries. Firstly, the input sequences of records become less complex (the maximal length of content plan is 92 compared to more than 800 for the original tables). Secondly, the records are ordered in the same way as they should appear in the summary. Puduppully et al. [2019] show that this approach led them to really promising results (e.g. they obtained BLEU score of about 16 which was an improvement of about 2 points over their Copy baseline).

5.5.1 Results

During generation we applied two different settings. Firstly we ignore the outputs from the Content Planning Decoder and use the *gold content plan.* (Since we have the gold content plans only for the training and validation parts of the dataset, the reported metrics are calculated only on the validation part) We can see that with gold content plans model mentions more than 70% of the entities that also appear in the gold summaries (we believe that the number would increase with better quality of the gold content plans[7]).

Figure 5.6 is a good example of the summaries which are generated from the *gold content plans.* Gold summary mentions 13 entities, out of which 12 are mentionned in the generated one. The generated text contains 39 numerical values out of which 31 are correct. The model learned to place the information about the entites in right[8] order, and to copy numbers related to entites. Many flaws still persist. The model generated 3 times the same information about *Richaun Holmes*[9] Another problem demonstrated in the summary is that model mixed up records about Toronto and about Philadelphia (e.g. model generates sentence : *"Defense was key for Toronto , as they held Philadelphia to 55 percent from the field and 68 percent from three - point range ."*, however 55% shooting for 2pt and 68% shooting for 3pt are the statistics related to Toronto).

The other generation setting is to use the generated content plans. However this is where we failed to obtain the same results as Puduppully et al. [2019]. We observed that the network fails to learn when to place <*EOS*> token in the content plan and the generated content plans end with a sequence of repetitions. Therefore the part of the model responsible for text generation (Content Plan

[7]Puduppully et al. [2019] extract the content plans with specialized information extraction system, and they claim that "strictly speaking, we cannot talk about gold content plans".

[8]The same order as in the gold summaries.

[9]Let me note that there is a numerical value *"11 points"* which is counted 3 times. (Therefore 3 is added to both *all the numerical values* and *correct numerical values.* This causes that reduplicated information has a big effect on the factual correctness metric.)

The Toronto Raptors defeated the Philadelphia 76ers , 122 - 95 , at philips arena on saturday . The Raptors were able to prevail with a win , as they outscored the sixers by 17 in the second quarter to pull out the win . Defense was key for Toronto , as they held Philadelphia to 55 percent from the field and 68 percent from three - point range . The sixers also dominated the rebounding , winning that battle , 44 - 30 . The sixers (4 - 14) have now lost 5 of their last 6 games , as this marks their fifth win in their last 6 games . Robert Covington was the lone bright spot for the sixers , as he tallied 20 points , 5 rebounds , 2 assists and 2 steals on 7 - of - 11 shooting . Jahlil Okafor was the only other blazer to score double figures , as he totaled 15 points and 5 rebounds . Sergio Rodriguez and Ersan Ilyasova each scored 11 points off the bench . Nik Stauskas was the only other starter in double figures , as he dropped 11 points . Richaun Holmes was the only other starter in double figures , as he dropped 11 points . Richaun Holmes was the only other starter in double figures , as he dropped 11 points . Richaun Holmes was the only other starter in double figures , as he dropped 11 points . Toronto will look to bounce back on sunday in a road matchup against the Orlando Magic . Toronto (11 - 6) have been dominant all season , but a win like this was their best performance of the season . Kyle Lowry once again carried the load , as he accumulated 24 points , 4 rebounds and 8 assists . Terrence Ross was second on the team , as he dropped 22 points on 8 - of - 11 shooting . DeMar DeRozan was the only other starter in double figures , as he accumulated 14 points , 5 rebounds and 5 assists . Jonas Valanciunas recorded a double - double , totaling 12 points and 11 rebounds .

Figure 5.6: A summary generated by the Content Selection and Planning model from the gold content plans. The corresponding gold summary and input table is shown in figure 1.1.

Encoder and Text Decoder) fails to produce reasonable texts as it generates from content plans with characteristics different to anything seen during training. Table 5.4 shows that model still achieved reasonable entity recall (in fact better than any previous model) and the best correctness, although the correctness is due to large number of repetitions of the accurate information.

Model	**Validation Perplexity**$_1$	**Validation BLEU**	**Test BLEU**	**Entity Recall**	**Factual Correctness**
CS&P$_G$	8.76	13.07	13.08	44.58%	67.76%
CS&P$^*_G$		22.8*	–	71.43%*	54.69%*

CS&P - Content Selection and Planning model

$_G$ - Greedy Decoding

$_1$ - Validation Perplexity of text decoded from gold content plans

* - All the metrics are computed only on the validation part of the dataset, with *gold content plans*

Table 5.4: Performance metrics on the Content Selection and Planning model.

Since we do not implement the Beam Search decoder for the content plans (due to shortness of time) we try to artificially add <*EOS*> token at some position in the generated content plan and mask everything after, however the results do not show any improvement. The same applies for using Beam Search in Text Decoder. (Therefore the results presented in table 5.4 are calculated on greedy decoded summaries generated from unmasked greedy generated content plans.)

5.6 Ordered Tables

Since we haven't managed to obtain satisfactory results using any of the previously proposed methods we try to make the task easier. Looking at the results of the CS&P model generating from the *gold content plans*, we may draw a conclusion that the performance bottleneck is in the understanding of the tabular structure.

Going through the gold content plans as well as the ones generated by Content Selection and Planning model we spotted that their structure follows a simple pattern. At first the teams are presented, then there is some information about the best players and about players who performed surprisingly well.

We order the input records as described in section 2.3.6 and train all of our models on the ordered sequences.

5.6.1 Results

We present only the results of the Copy model (at the time of writing the CopyCS model is on the verge of outperforming the Copy model according to validation perplexity, however we do not include its results due to shortness of time) on the ordered tables. In the following text we call the Copy model trained on the ordered tables $Copy_{ordered}$.

We cannot make any clear conclusions. We see a raise in terms of the BLEU score (of about 2 points compared to Copy model) but also a drop in both manually evaluated metrics. The overal performance of $Copy_{ordered}$ is comparable to CopyCS model and it is really unfortunate that we did not manage to train $CopyCS_{ordered}$[10] in time.

Model	**Validation Perplexity**	**Validation BLEU**	**Test BLEU**	**Entity Recall**	**Factual Correctness**
$\text{Copy}_{orderedG}$	9.21	12.98	13.32	–	–
$\text{Copy}_{orderedB5}$		13.75	14.01	33.73%	46.84%

$\text{Copy}_{ordered}$ - Joint-Copy model operating on the ordered tables
$_G$ - Greedy Decoding
$_{B5}$ - Beam search decoding, beam size = 5

Table 5.5: Performance metrics on the Content Selection and Planning model.

5.7 Shortened Tables

Our second effort to simplify the input tables is described in section 2.3.6. Basically we order the records and remove the unsignificant ones to obtain *a sequence of records similar to a content planned one*. We opted to train the *CopyCSBidir* model (discussed in section 4.4.2) as it is similar in architecture to *CS&P* model, which achieved promising results on the gold content plans. The hyperparameter configuration is shown in figure 5.7.

[10] $CopyCS_{ordered}$ is the *CopyCS* model trained on the ordered tables

Hidden States Dimensionality	**Learning Rate**	**Batch Size**
500	0.0001	8

Token	**Embedding Dimensionality**
record.type	300
record.home_away	300
record.value	500
record.entity	500
summary token	500

Figure 5.7: Hyperparameter settings for *CopyCSBidir*

5.7.1 Results

This configuration (more sophisticated model, input table that is easier to understand) achieved the best BLEU score of all the models (excluding the one generating from the gold content plans). Table 5.6 shows that we managed to improve the BLEU score by more than 1 point compared to both CopyCS and Copy$_{ordered}$ models. Model also learned to mention more players, however not with correct statistics. Since we reduced the amount of input records related to all but the best three players, the model learned to *hallucinate* the statements about the remainng ones. We haven't experimented with other possible combinations but we expect that the model performance would improve when about five best players would be fully described in the input tables (compared to actual three).

Model	**Validation Perplexity**	**Validation BLEU**	**Test BLEU**	**Entity Recall**	**Factual Correctness**
CopyCSBidir$_G$	11.24	14.31	14.45	–	–
CopyCSBidir$_{B5}$		15.18	15.63	50.6%	49.87%

CopyCSBidir - model introduced in section 4.4.2 trained on shortened sequences of input records.
$_G$ - Greedy Decoding
$_{B5}$ - Beam search decoding, beam size = 5

Table 5.6: Performance metrics on the Content Selection and Planning model.

This is our final experiment, using the most advanced preprocessing as well as the most advanced model architecture. Therefore I would like to show how far is our best model from the ideal generation system described in the introduction. The generated text in figure 5.8 starts by introducing the teams that have played as well as the score and the location where the match was played. Next it contains some "interesting" events that happened, followed by statistics of the players. Many generated summaries (although not this one) end with a phrase about future schedule of both teams. Since *Jahlil Okafor* isn't between the best three players of the match, *all his statistics excluding his points and assists are hallucinated*. Model mixed up *Robert Covington* with *Terrence Ross*, thus the presented statistics are not correct. We think that further hyperparameter tuning (adjusting the length of the sequence of input records, advanced learning rate strategies) may lead to improvements in all the metrics we measured.

The Toronto Raptors defeated the Philadelphia 76ers , 122 - 95 , at wells fargo center on saturday evening . The Raptors (11 - 6) came away with a 33 - point second quarter , where the Raptors (11 - 14) opened up a 12 - point lead by the end of the first quarter . The game remained close in the third quarter , as the Raptors outscored the sixers , 31 - 24 . Toronto was led by Terrence Ross , who poured in 22 points on 7 - of - 11 shooting , to go along with 8 assists and 4 rebounds , in 32 minutes . Robert Covington followed up with 22 points on 8 - of - 11 shooting , including 3 - of - 5 from long range , in 23 minutes off the bench . Jonas Valanciunas was solid with 12 points and 5 assists , while Terrence Ross chipped in 22 points on 8 - of - 11 shooting , including 3 - of - 5 from long range , in 23 minutes off the bench . The Raptors shot 55 percent from the field , while the 76ers shot just 42 percent from the field and 41 percent from long range . Jahlil Okafor was the high - point man for Philadelphia , with 24 points on 7 - of - 9 shooting , to go along with 8 assists and 4 rebounds , in 32 minutes . Jahlil Okafor followed up with 15 points , 5 rebounds , 5 assists and 2 steals , in 32 minutes .

Figure 5.8: A summary generated by the Copy$_{prunned}$ model. The corresponding gold summary and input table is shown in figure 1.1.

5.8 Overall Comparison

We start with the Baseline model (section 4.2) which produces fairly good language but many hallucinated statements (only 8% of the produced statements are correct).

Next we experiment with the Copy model (section 4.3). There we see the number of correct statements to increase to more than 40% and the BLEU score to rise by more than 2 points.

We move on to the *CopyCS* model (section 4.4.1). We see another improvement in the BLEU score (by 1 point) and the entity recall (by 5%) however the factual correctness decreases and the produced language still contains many contradictions.

The CS&P model (section 4.4) is the last one we use for the task. We see that the model achieves great performance on reduced and reorganized tables (the BLEU score bigger than 22) although the part of the model creating the reduced tables does not cooperate well with the part generating text, therefore we do not see any improvement over the *CopyCS* model when generating *end-to-end*.

Our last experiments aim to make the sequence of input records more organized and shorter. We train the *CopyCSBidir* model on the simplified input sequences, and manage to obtain the best BLEU score (increase by more than 1 point over *CopyCS* trained on unordered tables) and the best score on all manually evaluated metrics.

Model	**Validation Perplexity**	**Validation BLEU**	**Test BLEU**	**Entity Recall**	**Factual Correctness**
BR$_{B5}$	10.59	9.99	10.6	37.35%	8.03%
Copy$_{B5}$	9.87	12.19	12.5	39.76%	47.13%
CopyCS$_{B5}$	9.93	13.54	13.96	44.58%	42.22%
CS&P$_{G}$	8.76*	13.07	13.08	44.58%	67.76%
Copy$_{orderedB5}$	9.21	13.75	14.01	33.73%	46.84%
CopyCSBidir$B5$	11.24	15.18	15.63	50.6%	49.87%

BR - Baseline, regularized

Copy - Joint-Copy model

CopyCS - Joint-Copy decoder + Content Selection encoder

CS&P - Content Selection and Planning model

Copy$_{ordered}$ - Joint-Copy model operating on the ordered tables

CopyCSBidir - the model introduced in section 4.4.2

$_G$ - Greedy Decoding

$_{B5}$ - Beam search decoding, beam size = 5

* - Validation Perplexity of text decoded from gold content plans

Table 5.7: Performance metrics on all the models and approaches discussed in this chapter.

Conclusion

In this thesis, we explored document-scale text generation conditioned on the basketball match statistics. In chapter 1 we presented the RotoWire dataset. We analysed the statistics of the dataset and came up with numerous preprocessing and cleaning methods (chapter 2). In the rest of the thesis we focused on creating building blocks, composing them into models (chapters 3, 4) and evaluating and analysing the experiments (chapter 5).

We followed the path set up by Wiseman et al. [2017]. First we trained a baseline Encoder-Decoder model with Attention that produced texts of reasonable quality. However it suffered from severe *fact hallucinations* (e.g. the baseline learned to generate *some* number when describing how many points a player scored, instead of generating *the exact value*). Next, we added joint-copy mechanism to the Decoder part of the model, which caused massive improvement in terms of entity recall as well as factual correctness (the model is better at selecting important entities and produces correct facts about them).

Inspired by Puduppully et al. [2019], we experimented with Content Selection encoder + joint-copy decoder model (CopyCS), and with Content Selection and Planning model (CS&P). While both of the models helped to improve the quality of the generated summaries in terms of all measured metrics, we were not satisfied with the texts as they contained a lot of repetitions and in many cases they were not properly finished (the models did not learn to place correctly the <*EOS*> token). Our hypothesis is that it is caused by suboptimal hyperparameter settings, and a future work may be focused e.g. on applying learning rate decay, using layer normalization etc.

Analysing the content plans generated by CS&P model we hypothesized that the performance bottleneck may be the complexity of the input sequence of the records. Therefore we ordered the records and removed many unsignificant ones from the inputs and trained CS&P as well as the Copy models on the new data. The results prooved our hypothesis as we were able to obtain the highest BLEU score (which improved from 10 for the baseline to 15 for the CS&P model trained on shortened tables), the highest entity recall and second highest factual correctness out of all trained models.

The generated summaries did not fully match of our expectations. While our best model learned to extract information about the teams, it still suffers from selecting wrong players to talk about (as the entity recall for our best model is only about 50%), and copying wrong information (the factual correctness is on the same level as the entity recall).

We believe that future work should focus on improving the Content Planning mechansim, as we saw that CS&P model generating from gold content plans hugely outperformed our best model on the BLEU score (22.8 vs 15.1), the Entity Recall (71.4% vs 50.6%) as well as on the factual correctness (54.69% vs 49.87%). It might be of interest to use the Transformer architecture for text generation part of the task [Vaswani et al., 2017]. Specifically we are considering the few-shot setting with pretrained transformer language models [Chen et al., 2020].

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List of Tables

A. Implementation

We provide code implementing preprocessing methods as well as the neural network architectures. In this appendix we will shortly explain how to use attached code, and elaborate about the implementation.

First, let us note that the code was implemented and tested only on linux machines (on AIC cluster, on my personal computer and on `https://colab.research.google.com/`). The sources depend on *Tensorflow 2.x*, *NLTK 3.6*, *numpy 1.18*, *text2num 2.2*, and *python 3.8*.

A.1 User Documentation

The attached .zip file contains 2 directories, *preprocessing* and *neural_nets*. In this section we will discuss how to perform cleaning (section 2.7), preparation of the dataset, training of the models and generation of the output summaries.

RotoWire dataset can be downloaded from the original authors [Wiseman et al., 2017] (`https://github.com/harvardnlp/boxscore-data`), the content plans used for *CS&P* model (section 4.4) are available at google drive[1] provided by Puduppully et al. [2019].

A.1.1 Cleaning

We documented in section 2.7 that the original dataset contains many summaries which are not closely related to the input tables. `preprocessing/erase_faults.py` traverses the .jsons in the dataset and erases all that we consider faulty, and save the cleaned dataset to new files.

A.1.2 Preparation of Content Plans

The content plans by Puduppully et al. [2019] contain some data points which we consider faulty, and use different notation of entities, values etc. Therefore we provide script `preprocessing/prepare_content_plans.py` which transforms the content plans by Puduppully et al. [2019] to a form which we can use for creation of the Dataset.

A.1.3 Creation of the Dataset

We train our models on special tensorflow format of the datasets[2]. Running script `preprocessing/create_bpe_dataset.sh` from the *preprocessing* directory we can create *.tfrecord* datasets.

The script accepts three positional command line arguments: number of merges in Byte Pair Encoding (discussed in section 2.6), directory where to save the dataset and directory with the original dataset. The optional arguments provide following options:

[1]`https://drive.google.com/drive/folders/1R_82ifGiybHKuXnVnC8JhBTW8BAkdwek` We use the content plans from the *inter* directory.

[2]`https://www.tensorflow.org/tutorials/load_data/tfrecord`

- `--adv` : lowercase the dataset
- `--content_plan` : create the dataset with the content plans (for training of the *CS&P* model)
- `--order_records` : order the records as explained in section 2.3.6
- `--prun_records` : order the records and erase the unsignificant ones (section 2.3.6)
- `--tfrecord` : save the dataset to *.tfrecord* format
- `--npy` and `--txt` serve only debugging purposes

A.1.4 Training of the Models

Having prepared the dataset, we can start training any of the models discussed in the thesis by running `train.py` script. It accepts numerous command line arguments that are described after calling `train.py --help`.

We also show an example how to train the baseline model discussed in section 5.2 (assuming the prepared dataset is in directory `ni_tfrecord`):

```
python3 train.py --path=ni_tfrecord --batch_size=8 \
    --word_emb_dim=600 --tp_emb_dim=300 --ha_emb_dim=300 \
    --hidden_size=600 --attention_type=dot \
    --decoder_type=baseline --truncation_size=100 \
    --truncation_skip_step=25 --dropout_rate=0.3 \
    --scheduled_sampling_rate=0.8
```

A.1.5 Generation with Trained Model

After having trained the model we can use `generate.py` script to generate summaries of all the tables from the validation and test dataset. It is important to note that even a slight change in the dataset files may result in broken generation, therefore we advise the reader to use exactly the same dataset both for training and for generation.

To allow generating with the models presented in this thesis we publish all the models along with datasets used for their training on google drive[3] along with exact instructions how to set up the hyperparameters.

A.2 Implementation Details

Tensorflow defines two modes of computation. One can either define a computational graph (`https://www.tensorflow.org/guide/intro_to_graphs`) or compute eagerly (`https://www.tensorflow.org/guide/eager`). We opted to use the best of both worlds. Since training in *graph mode* is significantly faster

[3]`https://drive.google.com/drive/folders/1eRzAOaZ2SLHOiYm2xtazsb3XSc5ILgbv?usp=sharing`

and more memory efficient, we train our models in *graph mode*. During evaluation and inference we use *eager mode* which allows usage of external libraries and python code. In this section we show where an interested reader may find our implementations of the models and architectures discussed in this thesis.

The implementation of training, inference and evaluation of all the models generating end-to-end can be found in file `neural_nets/baseline_model.py`. CS&P model is implemented in `neural_nets/cp_model.py`. The following listing explains the contents of other scripts from the directory:

- `neural_nets/encoders.py` : baseline Encoder, Encoder with Content Selection, Encoder with Content Selection and bidirectional LSTM
- `neural_nets/layers.py` : feed-forward network processing the input records, both types of attention (dot, concat, discussed in section 3.2.2), Content Selection mechanism, Content Planning mechanism, baseline Decoder, Joint-Copy Decoder
- `neural_nets/training.py` : a set up script that creates models and starts training
- `neural_nets/callbacks.py` : two callbacks which are called at the end of each epoch of training, *CalcBLEUCallback* which generates summaries from a subset of a dataset and reports the BLEU score, *SaveOnlyModelCallback* which saves model without optimizer
- `neural_nets/beam_search_adapter.py` : our implementation of the Beam Search