Learning Meters of Arabic Poems with Deep Learning

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CERTIFICATION OF APPROVAL

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Thesis Outline

The coming chapters are arranged as follows:

- Chapter 1: Presents some basic introduction and background knowledge as regards the Arabic Poem and its definitions. Also, it contains details about the Arabic language and some feature used during our work.
- Chapter 2: Introduces the essential pre-processing steps, and the justification for their need. Pre-processing steps are data extraction, data cleansing and data format.
- Chapter 3: introduces the data encoding techniques used and the effect of each one. Also, it contains some comparisons between the three techniques used.
- Chapter 4: presents the model's details and how we chose the model and the architecture and hyper-parameters details.
- Chapter 5: Results and discussion.
- Chapter 6: Conclusion and future work

ABSTRACT

People can easily determine whether a piece of writing is a poem or prose, but only specialists can determine the class of poem.

In this thesis, We built a model that can classify poems according to their meters; a forward step towards machine understanding of Arabic language.

A number of different deep learning models are proposed for poem meter classification. As poems are sequence data, then recurrent neural networks are suitable for the task. We have trained three variants of them, LSTM, GRU with different architectures and hyper-parameters. Because meters are a sequence of characters, then we have encoded the input text at the character-level, so that we preserve the information provided by the letters succession directly fed to then models. Besides, We introduce a comparative study on the difference between binary and one-hot encoding regarding their effect on the learning curve. We also introduce a new encoding technique called *Two-Hot* which merges the advantages of both *Binary* and *One-Hot* techniques.

Artificial Intelligence currently works to do the human tasks such as our problem here. Our target in this thesis is to achieve the human accuracy which will make it easy for anyone to know the meter for any poem without referring to the language experts or to study the whole field to achieve it.

In this thesis, We will explain how to use the deep learning to classify the Arabic poem to classes. Also, explain in details the feature of Arabic poem and how to deal with this features. Besides, We explain how can anyone work with Arabic text encoding with a dynamic way to encode the text at the character level and deal with the Arabic text feature example the *Tashkeel*.

Chapter 1

INTRODUCTION

Arabic is the fifth most widely spoken language[1]. It is written from right to left. Its alphabet consists of 28 primary letters, and there are 8 more derived letters from the basic ones, so the total count of Arabic characters is 36 characters. The writing system is cursive; hence, most letters join to the letter that comes after them, a few letters remain disjoint.

1.1 Arabic Poetry

Arabic poetry(الشعر العربي) is the earliest form of Arabic literature. It dates back to the Sixth century. Poets have written poems without knowing exactly what rules which make a collection of words a poem. People recognize poetry by nature, but only talented ones can write poems. This was the case until *Al-Farahidi* (718 786 CE) has analyzed the Arabic poetry, then he came up with that the succession of consonants and vowels produce patterns or *meters*, which make the music of poetry. He has counted them fifteen meters. After that, a student of *Al-Farahidi* has added one more meter to make them sixteen. Arabs call meters بحور which means "*seas*". The study of Arabic Poems classification is named **Al-Arud (العَروض)**. It takes too much time for anyone to be an expert in this field.

1.2 Deep Learning

Deep Learning also named Deep Neural Network is part of Machine Learning algorithms. Deep Learning is trying to simulate the human brain into Neural dependency. Using Deep Learning, we can achieve better learning results from the data. Deep Neural Network needs a huge amount of data to achieve the expected learning curve

[1] *according to the 20th edition of Ethnologue, 2017*

and results. It also needs a massive amount of computation to build the networks which are based on an artificial neural network. We used the Recurrent Neural Network (RNN) to work on the Arabic Text which shown its ability to achieve outstanding performance over the text problem data. We also used LSTM to solve the long dependency issue in RNN. We will go deep into the Background section (add deep learning section reference).

1.3 Thesis Objectives

In this study, we work to classify the poem and utilize the latest technologies check the class of poem. We also worked to achieve near human expert results which make our work is a breakthrough in the field concerning the results compared to the current achieved results. Figure 1.1 shows the steps.,

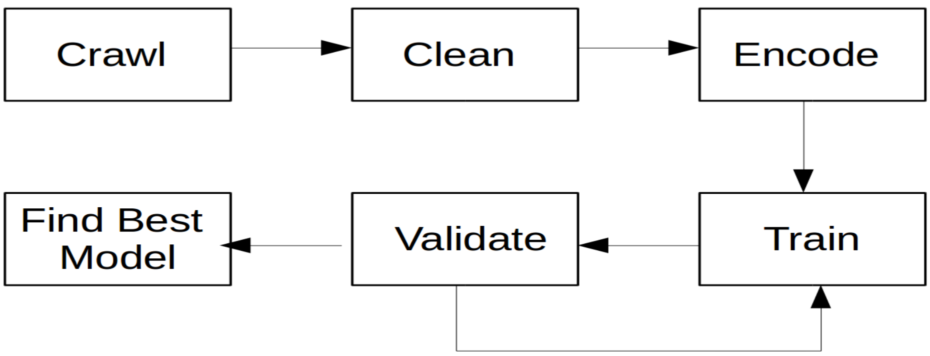

Figure 1.1: Thesis Working Steps.

- Crawling the data from the available sources with labeling.
- Clean and transform the data.
- Encode the data into a way to be input to the model to work on it. We used many encoding methods and compared each of them.
- Train the RNN model into the cleaned data.
- Validate and test the model.
- Enhance the model.

Chapter 2

BACKGROUND

Each Arabic letter represents a consonant, which means that short vowels are not represented by the 36 characters, for this reason, the need of *diacritics* rises. *Diacritics* are symbols that comes after a letter to state the short vowel accompanied by that letter. There are four diacritics ◌َ ◌ُ ◌ِ ◌ْ which represent the following short vowels /*a*/, /*u*/, /*i*/ and *no-vowel* respectively, their names are *fat-ha, dam-ma, kas-ra and sukun* respectively. The first three symbols are called *harakat*. Table 2.1 shows the 4 diacritics on a letter.

Diacritics	*without*	*fat-ha*	*kas-ra*	*dam-ma*	*sukun*
Shape	د	دَ	دِ	دُ	دْ

Table 2.1: *Diacritics on the letter* د

There are two more sub-diacritics made up of the basic four to represent two cases:

Definition 1 ***Shadaa***
to indicate the letter is doubled. Any letter with shaddah (ّ) the letter should be duplicated: first letter with a constant (sukoon) and second letter with a vowel (haraka) [75]; Table 2.2 shows the dal with shadda and the original letters.

Diacritics	*letter with Shadda*	*letters without shadaa*
Shape	دَّ	دْدَ

Table 2.2: *Shadaa diacritics on the letter* د

Definition 2 ***Tanween***
is doubling the short vowel, and can convert Tanween fathah, Tanween dhammah or Tanween kasrah by replacing it with the appropriate vowel (dhammah, fathah or kasrah) then add the Noon letter with constant to the end of the word [75]. Table 2.3 shows the difference between the original letter and the letter with Tanween

Diacritics	*letter with tanween*	*letters without tanween*
Tanween Fat-ha	دً	دَ+نْ
Tanween Dam-ma	دٌ	دُ+نْ
Tanween Kas-ra	دٍ	دِ+نْ

Table 2.3: *Tanween diacritics on the letter* د

Arabs pronounce the sound */n/* accompanied *sukun* at the end the indefinite words, that sound corresponds to this letter نْ, it is called *noon-sakinah*, however, it is just a phone, it is not a part of the indefinite word, if a word comes as a definite word, no additional sound is added. Since it is not an essential sound, it is not written as a letter, but it is written as *tanween* ◌ٍ ◌ً ◌ٌ. *Tanween* states the sound *noon-sakinah*, but as you have noticed, there are 3 *tanween* symbols, this because *tanween* is added as a diacritic over the last letter of the indefinite word, one of the 3 harakat*harakat* accompanies the last letter, the last letter's *harakah* needs to be stated in addition to the sound *noon-sakinah*, so *tanween* is doubling the last letter's *haraka*, this way the last letter's *haraka* is preserved in addition to stating the sound *noon-sakinah*; for example, نْ + رَجُلُ is written رَجُلٌ and نْ + رَجُلِ is written رَجُلٍ.

Those two definition, Definition 1 and Definition 2 will help us to reduce the dimension of the letter's feature vector as we will see in *preparing data* section.

Diacritics makes short vowels clearer, but they are not necessary. Moreover, a phrase without full diacritics or with just some on some letters is right linguistically, so it is allowed to drop them from the text.

In Unicode, Arabic diacritics are standalone symbols, each of them has its own unicode. This is in contrast to the Latin diacritics; e.g., in the set *{ê, é, è, ë, , , }*, each combination of the letter *e* and a diacritic is represented by one unicode.

2.1 Arabic Arud Science

reference is the book .... to be added

Definition 3 ***Arud***
In Arabic Arud natively has many meanings (the way, the direction, the light clouds and Mecca and Madinah[1]*. Arud is the science which studies The Arabic Poem meters and the rules which confirm if the Poem is sound meters & broken meters. It named Arud because some people said he put this science in Arud place* العَروض *with fat-ha, not with dam-ma such as the science name* العُروض *between Mecca and Madinah.*

The Author of this science is *Al-Farahidi* (718 786 CE) has analyzed the Arabic poetry; then he came up with that the succession of consonants and vowels produce patterns or *meters*, which make the music of poetry. He was one of the famous people who know The melodies and the musical parts of speech. He has counted them fifteen meters. After that, a student of *Al-Farahidi* has added one more meter to make them sixteen. Arabs call meters بحور which means "*seas.*" Poets have written poems without knowing exactly what rules which make a collection of words a poem.

The Reasons which makes *Al-Farahidi* put this science is

- Protect the Arabic Poems from the broken meters.
- Distinguish between the original Arabic Poem and the non-poem or from the prose.
- Make the rules clear and easy for anyone who needs to write a poem.

Some people said that the one-day Al-Farahidi was walking into the metal-market and he was said some of the poems and for some reasons the knock of the metals matched the musical sound of the poem he was saying then he got an idea to explore the Arud of the poems.

[1] *Mecca and Madinah are two cities in Saudi Arabia.*

2.1.1 Feet Representation

A meter is an ordered sequence of feet. Feet are the basic units of meters; there are ten of them.

Definition 4 ***Feet***
A Foot consists of a sequence of ***Sukun*** *(Consonants) represented as (0) and* ***Harakah*** *(Vowels) (/). Traditionally, feet are represented by mnemonic words called tafail تفاعيل.*

Feets consists of three parts (Reasons أسباب, Wedge وتد, Breaks فواصل).

- **Reasons (أسباب)**: It has two types
  1. **Light (سبب خفيف)** which happens when we have the first letter is harakah and the second is sukun (/0) example (هَبْ, لَمْ).
  2. **Heavy (سبب ثقيل)** which happens when we have two harakah letter (//) example (لَكَ, بِكَ).
- **Wedge (وتد)**: It has two types
  1. **Combined Wedge (وتد مجموع)** which happens when we have two harakah letters followed by sukun (//0) example (مَشَى, عَلَى).
  2. **Separated Wedge (وتد مفروق)** which happens when we have two harakah and in between a sukun letter (/0/) example (مُنْذُ, مِصْرُ).
- **Breaks (فواصل)**: It has two types
  1. **Small Break (فاصلة صغرى)** which happens when we have three harakah letters followed by a sukun letter (///0) example (ذَهَبُوا, سُفُناً).
  2. **Big Break (فاصلة كبرى)** which happens when we have four harakah letters followed by a sukun letter (////0) example (جَعَلَهُمْ).[2]

[2] *Some of Arab linguistic scientist assume the small Breaks as a combination between big reason and small reason. Same for the Big Breaks assumed to be a combination between Big reason and Combined Wedge. So, they didn't assume we have three types of feet it is only pure two and any other feets constructed from this two. In this thesis we assume there are three feets .*

2.1.1.1 Rules for Arabic Letters Representation

Arabic letter has one general rule in the poem representation which is we represent only the letters which is (spoken) not the written which means the letters with phonatics not the written. We have give the below rules as a results of the general rule.

- Any letter with *harakah* represented as (/).
- Any letter with *sukun* represented as (0).
- Any letter with shaddah represented by two letters the first one will be *sukun* and the second letter will be *harakah* represented as (0/) example (مُحَمَّد) will be (//0//0).
- Any letter with tanween represented by two letters the first one is *haraka* (/) and the second is *sukun*.
- Alef without hamze (همزة الوصل) and Wow Algmaa are not represented example (وُاعلَموا) will be (/0//0)
- If we have a letter which is not written but (spoken) so, we will represent it example (هذا) it include Alef but not written (هاذا) the representation will be (/0/0).
- If we have *Meem Aljamaa* with harakah so, it represented with *Mad* example (هُمُ) will be (//0) .
- *Alef Mad* (آ) will be two letters *Alef with harakah* and *Alef with sukun* example (آدَمُ) will be (/0//).
- if the verse ended with *harkah* we will add *sukun* to it.

Exampel: (note: the below representation is not complete)

وَجَدتُ الناسَ مَيتاً مِثلَ حَيٍّ *** بِحُسنِ الذِكرِ أَو حَيّاً كَمَيتِ
وَجَدْتُنُنَاْ سَمَيْتَنْمِثْ لَحَيْيِنْ *** بِحُسْنِذْذِكْ رِأَوْحَيْيَنْ كَمَيْتِيْ

2.1.2 Arabic Poetry Feets

Arabic poetry feets has ten tafa'il تفاعيل (scansion) any peom constructed from these feets. They are eight from writing (syntax) prespective, But it ten in the rules.

#	Feet	Scansion	Construction
1	فَعُولُنْ	0/0//	combined wedge (فعو) and small reason (لن)
2	مَفاعِيلُنْ	0/0/0//	combined wedge (مفا) and two light reasons (عي) (لن)
3	مُفَاعَلَتُنْ	0///0//	combined wedge (مفا), heavy reason (عل) and light reason (تن)
4	فَاعِلاَتُنْ	0/0//0/	light reason (فا), combined wedge (علا) and light reason (تن)
5	فَاعِ لاتُنْ	0/0//0/	Separated wedge (فا ع) and two light reason (لا)(تن) [3]
6	فَاعِلُنْ	0//0/	light reason (فا) and combined wedge (علن)
7	مُتَفَاعِلُنْ	0//0///	heavy reason (مت), light reason (فا) and combined wedge (علن)
8	مَفْعُولاَت	0//0///	two light reason (مف)(عو) and separated wedge (لات)
9	مُسْتَفْعِلُنْ	0//0/0/	two light reason (مس)(تف) and combination wedge (علن)
10	مُسْتَفْعِ لُنْ	0//0/0/	light reason (مس), separated wedge (تفع) and light reason (لن)[4]

Table 2.4: The ten feet of the Arabic meters.

[3] *We separated the letters (ع) and (لا) in (فا ع لاتن) to show that this part is separated wedge and distinguish between this feet and (فا ع لاتن) which contains combined wedge .*

[4] *We separated the letters (ع) and (ل) in (مستفع لن) to show that it ends with a separated wedge and distinguish between this feet and (مستفعلن) which contains combined wedge*

Definition 5 ***Meter***
Poetic meters define the basic rhythm of the poem. Each meter is described by a set of ordered feet which can be represented as ordered sets of consonants and vowels [76].

ولد الهدى فالكائنات ضياء *** وفم الزمان تبسم وثناء انشاء
الروح والملأ الملائك حوله *** للدين والدنيا به بشراء

Definition 6 ***Arabic Verse***
refers to "poetry" as contrasted to prose. Where the common unit of a verse is based on meter or rhyme, the common unit of prose is purely grammatical, such as a sentence or paragraph [5]. A verse know as Bayt in Arabic بيت

Definition 7 ***Shatr***
A verse consists of two halves, each of them is called shatr and carries the full meter. We will use the term shatr to refer to a verse's half; whether the right or the left half.

Definition 8 ***Poem***
is a set of verses has the same meter and rhyme.

[5] *https://en.wikipedia.org/wiki/Verse_(poetry).*

2.1.3 Arabic Poetry Meters

2.1.3.1 Al-Taweel

Al-Taweel is named Al-Taweel for two reasons; first, It is the longest meter between all meters. Second, It starts with Wedge then Reasons and Wedge is longer than Reasons. So, it named Al-Taweel. We need here to note later in the encoding section we will pad all other meters by zeros to make it all the same length. Example if the max Bayt is 82 so, any Bayt less than 82 will be padded by zeros to have the same length.

Example Of Al-Taweel:

اذا جادَ أقوامٌ بِمالِ رأَيْتَهُمْ *** يَجودونَ بالأرواحِ مِنْهُم بلا بُخلِ
0/0/0// 0/0// 0/0/0// 0/0// *** 0//0// 0/0// 0/0/0// 0/0//
فعلون مفاعيلن فعولن مفاعلن *** فعولن مفاعيلن فعولن مفاعيلن

2.1.3.2

Chapter 3

DATASET

We have scrapped the Arabic dataset from two big poetry websites: الديوان[1], الموسوعة الشعرية[2]. Both are merged into one large dataset. It is important to note that the verses' diacritic states are not consistent, this means that a verse can carry full, semi diacritics or it can carry nothing. The total number of verses is 1,862,046 poetic verses; each verse is labeled by its meter, the poet who wrote it, and the age which it was written in. There are 22 meters, 3701 poets and 11 ages; and they are Pre-Islamic, Islamic, Umayyad, Mamluk, Abbasid, Ayyubid, Ottoman, Andalusian, era between Umayyad and Abbasid, Fatimid and modern. We are only interested in the 16 classic meters which are attributed to *Al-Farahidi*, and they are the majority of the dataset with a total number of 1,722,321 verses[3].

3.1 Preparing Data

3.1.1 Data Cleaning

[1] *aldiwan.net*
[2] *poetry.tcaabudhabi.ae*
[3] https://wwww.github.com/tahamagdy

Chapter 4

DATA ENCODING

4.0.1 Arabic Poem Encoding

4.0.1.1 One-Hot encoding

4.0.1.2 Binary Encoding

4.0.1.3 Two-Hot encoding

Chapter 5

MODEL TRAINING

Chapter 6

RESULTS AND DISCUSSION

Chapter 7

CONCLUSION AND FUTURE WORK

7.1 Future Work

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APPENDICES

APPENDIX A

Phase Correlation Theory

Let $D_1(x, y)$ and $D_2(x, y)$ be the dilated images to be registered, the Fourier transform for both $F_1(u, v)$ and $F_2(u, v)$ is given by:

$$F_k(u, v) = \mathcal{F}\{D_k(x, y)\}$$

$$= \int_{y=-\infty}^{y=\infty} \int_{x=-\infty}^{x=\infty} D_k(x, y) \exp^{(-i2\pi\omega xy)} \, dxdy \tag{7.1}$$

where, $\mathcal{F}$ is the Fourier operator, K denotes image 1 or 2, ω is the frequency (in hertz), x and y are the spatial domain coordinates, u and v are the frequency domain coordinates of the two images.

Given two images of size $N \times M$ shifted against each other, according to the Fourier shift property, their Fourier becomes:

$$F_2(u,v) = F_1(u,v)\exp^{\left(-i2\pi\left(\frac{u\Delta x}{M}+\frac{v\Delta y}{N}\right)\right)} \tag{7.2}$$

The Normalized Cross Power Spectrum $(C(u,v))$ is defined as:

$$C(u,v) = \frac{F_1(u,v)\cdot F_2(u,v)^*}{|F_1(u,v)\cdot F_2(u,v)^*|} \tag{7.3}$$

where '.' denotes the element-wise product, '*' denotes the complex conjugate.

Using equation 7.2:

$$C(u,v) = \frac{F_1(u,v)\cdot F_1(u,v)^*\exp^{\left(i2\pi\left(\frac{u\Delta x}{M}+\frac{v\Delta y}{N}\right)\right)}}{\left|F_1(u,v)\cdot F_1(u,v)^*\exp^{\left(i2\pi\left(\frac{u\Delta x}{M}+\frac{v\Delta y}{N}\right)\right)}\right|} \tag{7.4}$$

Since the phase term of $F_1(u,v)\cdot F_1(u,v)^*$ is zero, only the magnitude remains, i.e. $F_1(u,v)\cdot F_1(u,v)^* = |F_1(u,v)\cdot F_1(u,v)^*|$ and since the magnitude of any complex exponential is 1, the equation drops to:

$$C(u,v) = \frac{|F_1(u,v)\cdot F_1(u,v)^*|\exp^{\left(i2\pi\left(\frac{u\Delta x}{M}+\frac{v\Delta y}{N}\right)\right)}}{|F_1(u,v)\cdot F_1(u,v)^*|}$$

$$= \exp^{\left(i2\pi\left(\frac{u\Delta x}{M}+\frac{v\Delta y}{N}\right)\right)} \tag{7.5}$$

the inverse Fourier transform of which is a delta function, i.e. a single peak.

The Normalized Cross Correlation (c) equals:

$$c = \mathcal{F}^{-1}\{C\} = \delta(x + \Delta x, y + \Delta y) \tag{7.6}$$

The shift in x and y between the two images $(\Delta x, \Delta y)$ takes the location of the maximum peak in c, such that:

$$(\Delta x, \Delta y) = \underset{x,y}{\operatorname{argmax}}\{c\} \tag{7.7}$$