Case-Based Approach to Automated Natural Language Generation for Obituaries

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Abstract. Automated generation of human readable text from structured information is challenging because grammatical rules are complex making good quality outputs difficult to achieve. Textual Case-Based Reasoning provides one approach in which the text from previously solved examples with similar inputs is reused as a template solution to generate text for the current problem. Natural language generation also poses a challenge when evaluating the quality of the text generated due to the high cost of human labelling and the variety in potential good quality solutions. In this paper, we propose two case-based approaches for reusing text to automatically generate an obituary from a set of input attribute-value pairs. The case-base is acquired by crawling and then tagging existing solutions published on the web to create cases as problem-solution pairs. We evaluate the quality of the text generation system with a novel unsupervised case alignment metric using normalised discounted cumulative gain which is compared to a supervised approach and human evaluation. Initial results show that our proposed evaluation measure is effective and correlates well with average attribute error evaluation which is a crude surrogate to human feedback. The system is being deployed in a real-world application with a startup company in Aberdeen to produce automated obituaries.

Keywords: Natural Language Generation • Textual CBR • Text Evaluation

1 Introduction

Text generation is a common requirement for problem-solving in variety of tasks and domains, such as completing medical notes, compiling incident reports, and presenting weather forecasts [5,8,11]. These use-case examples typically have a common problem representation in that the generated text is the combination of the structured data (a set of pre-defined attribute values) and textual content, required to improve human readability. In this paper we address a similar task in which a text generation system is required to automatically generate an obituary based on information about the deceased's life. The information typically

includes: personal details; relationships, such as next-to-kin, spouse, children, friends; and details about funeral arrangements for the funeral or memorial.

The effectiveness of text generation system depend on the quality of the text produced, in terms of accuracy and readability, as well as the diversity of texts generated from the system. One approach is to use a standard abstract template with all the pre-defined attributes available as slots to be filled. But having a single template for every problem are difficult to construct for complex scenarios and result in very repetitive text outputs. Textual Case Based Reasoning (TCBR) gives an opportunity to develop dynamic templates with diverse text by re-using previous experiences.

In general, a TCBR system has a case-base containing information about previous experiences as its central knowledge source, which is used together with other key knowledge sources: the case representation and similarity knowledge [13]. In combination these knowledge sources enable the retrieval of similar cases from the case-base, providing a mechanism to re-use knowledge captured in previous examples to solve a new problem. Thus TCBR, as with CBR more generally, relies on the basic principle that "similar problems have similar solutions" [1]. Supervised Machine Learning approaches take advantage of this principle to learn more tailored representation or retrieval knowledge in order to improve some evaluation metric e.g. accuracy. However, in TCBR learning from labelled solutions is difficult because each solution tends to be unique and so simple feedback metrics are not so easily available to either refine or evaluate developing systems. We introduce a novel approach to evaluation that measures the extent to which similar problems have similar solutions by investigating the alignment between local neighbourhoods in the problem and solution space. This approach reduces the requirement for human evaluations.

In this work we generate a case-base by crawling the web to extract obituaries from Funeral Notices websites [3]. The information extracted from the website is plain text and needs pre-processing for building the case-base. In particular generating a structured representation in a knowledge rich manner. By manually analysing the processed obituaries, relevant attribute are identified to provide alternative representations for the problem component of the cases. An unsupervised evaluation technique is developed to evaluate the alternatives.

The main contributions of the work are as follows:

1. developing a real world system based on our TCBR approach for automatically generating obituaries which is being deployed by a start-up company;
2. a novel technique for evaluation of text generation in TCBR employing a case alignment approach using normalised discounted cumulative gain; and
3. demonstrating the effectiveness of the approach with experiments and comparison of results with other baselines and a average attribute error as a crude surrogate to human feedback.

The rest of the paper is organised as follows. The problem domain is discussed in more detail in section 2 before relevant related works are highlighted

[3] https://funeral-notices.co.uk/

in the section 3. The proposed case-based methodology for generation of textual obituaries identifies our alternative approaches to representation and similarity measuring in section 4. The experimental design is discussed in section 5, where we also introduce our novel evaluation method. In the section 6, we discuss the results obtained from our experiments, before concluding the paper and looking at future works in section 7.

2 Obituary Generation

An obituary is a written announcement of someone's death which is traditionally published in a local newspaper to inform the wider community about the death. It generally outlines the life and personality of the deceased person and provides the details of the funeral arrangements and memorials. In the growing digital era, people are tending towards using digital website to publish the obituaries instead of local newspapers to expand the audience from a local community to the wider world on the internet.

There are approximately 57,000 deaths in Scotland each year, of these two sites are providing obituaries notices currently. The main site captures only 10% of all death notices. There is an opportunity to improve the service provided and to integrate the latest AI technologies to support Funeral Directors to help the next of kin with the creation of digital public obituary notices.

Our commercial partner is in the process of providing a publication platform for obituary generation that focuses on supporting a sympathetic acknowledgement of the recently departed as a digitisation of the traditional print obituaries. In this paper, we investigated utilising a TCBR approach to generate dynamic and individual obituaries that help the next of kin prepare their tribute. The aim is to achieve a two-minute publication timeline, through an intuitive form that will lead to the generation of five bespoke obituary options, the undertaker and family can select the appropriate option with the ability to edit as required. New solutions generated on the system can be retained to increase the case-base size and diversity of solutions available.

A large number (around 100k) of obituaries, dating back to the year 2000, have been crawled and extracted from the web. As initial pre-processing, 30k obituaries created after 2015 are selected and out of these, the top 1000 notices based on those with higher word count is selected. After analysing this data an obituary can be divided into at least three distinct components: the personal information component; the relationships component; and funeral component.

1. **Personal Information**: this component gives the personal details of the deceased person, e.g. name, age, date and place of death, and cause of death. It can also include the information about the person's home town or previous working places, as well their hobbies.
2. **Relations**: this component presents the relatives' details, e.g., spouse, children, grand children, or in-laws. This component may also contain an emotional message about the family & friends and how the person is going to be missed by all who knew them.

3. **Funeral**: this component provides the details of funeral arrangements and will typically have the date, time and place for the memorial service. The component will also provide the information about the delivery of flowers and the potential guest list. For example, flowers may only be welcome from family members but all the friends and relatives are welcome to join at the memorial service. Options for donations and charity name can also be provided in this section in the lieu of flowers.

The main task for this project is to generate five diverse textual messages (obituary) based on the features given by the user. A simple message can be generated using an abstract template but then there will be no diversity in the generations and all the obituaries will become monotonous. The challenge is to generate human readable natural text which includes (almost) every feature to the generation and is diverse in nature as well.

3 Related Works

Automated generation of human readable text from unstructured data has been studied in various domains [8,5,12]. The studies mainly focus on the difficulties of mapping unstructured text from previous experience to a structured representation, measuring semantic or synaptic similarity for the retrieval & reuse of previous cases and automated evaluation of the generated text.

3.1 Text Generation

In [2], the author proposed a CBR system to generate weather forecast texts using examples from previous cases with similar weather states. For the retrieval of similar cases it is necessary to have same number of weather states in the retrieved one and the input query. The system fails to return a result if there's any mismatch in the number of states in input query and previous similar data. The system uses NIST5 score for evaluation requiring substantial reference texts for better performance. In [4] the textual summary of time series were generated using an end-to-end CBR system. The summary generation involved two steps where first an abstraction of time series is generated which in turns help the system to generate the textual summary of that abstraction. The system generated text was evaluated using a modified version of the edit distance measure [9] which heavily relies on the domain specifications. This is a custom evaluation approach that is difficult to use across different TCBR domains.

3.2 Case Alignment

There have been several approaches to measuring the performance of unsupervised CBR systems which focus on measuring the extent to which the problem-side space and solution-side space of case representation align with each other. In [6], authors proposed a case cohesion alignment to evaluate the performance

of a CBR system which measures the level of overlap in retrieval set. However, the method requires a trial and error approach to set up a threshold for selecting the number of nearest neighbours in both the sets. A mechanism of case alignment was presented in [8] where the alignment was measured by taking the average solution similarity of its neighbours weighted by their problem-side similarities. Authors in [16] modified the case alignment measure by utilising the case ranking of similar cases in problem and solution sets by using a modified version of Kendall tau distance. Although the method works well in several CBR problems, it fails to scale in a TCBR scenario [16].

In this work, previous examples are marked up to act as dynamic templates which can be populated with structured data to generate good quality, diverse natural text. Alternative representations and similarity measures are compared. We also evaluate the quality of the generated text with a problem-solution alignment measure but propose a novel, domain independent metric taken from information retrieval.

4 Case-Based Methodology

Central to developing a CBR system is the availability of experiential knowledge that can provide previously solved successful examples for reusing to solve new problems. The crawled examples from the web provide a suitable source of past examples. However as obituaries in natural language they provide a case solution example but not with separate problem and solution representations required for CBR systems. The first task in developing a TCBR system is to create a case representation to effectively capture case knowledge as associated problem and solution components. The second stage is to develop a similarity metric utilising the problem representation to support retrieval.

4.1 Case Representation

In TCBR, cases are generally represented in two parts: problem and solution component. The problem representation comprises a set of attributes whose values can either be extracted from the crawled obituaries or are known for a new problem. The solution representation is the natural language text of the obituary but may be considered as a template with the associated problem attribute values identifed and replaced by mark-up tags.

For example given an obituary: "*OLIVIA WILSON, Peacefully on the 14th May 2019 at home, Olivia of Patna. Beloved wife to the late James Wilson, much loved mum to Jack and partner Emily, gran to Ava, Lucy and Logan, loving aunt, sister and a friend to all. Funeral service will be help at Patna Kirk, Patna on Monday 26th May, 2019 at 11.00am and thereafter to Patna Cemetery to which all friends are respectfully invited. Donations if desired to Cancer Research UK and Strathcarron Hospice.*". Figure 1 shows the problem component of the case representation as a set of attribute-value pairs in marked-up XML format.

```
<obit>
    <personal_info_component>
        <name>OLIVIA WILSON</name>,
        <demise_how>Peacefully</demise_how> on the
        <demise_date>14th May 2019</demise_date> at
        <demise_place>home</demise_place>,
        <nick_name>Olivia</nick_name> of
        <home_town>Patna</home_town>.
    </personal_info_component>
    <relations_component>
        Beloved
        <spouse_gender>wife</spouse_gender> to
        <spouse_name>the late James Wilson</spouse_name>, much loved
        <parent_gender>mum</parent_gender> to
        <children_name>Jack</children_name> and partner
        <children_in_law_name>Emily</children_in_law_name>,
        <grandparent_gender>gran</grandparent_gender> to
        <grandchildren_name>Ava, Lucy and Logan</grandchildren_name>, loving
        <other_relations_types>aunt</other_relations_types>,
        <siblings_gender>sister</siblings_gender> and a friend to all.
    </relations_component>
    <funerla_component>
        Funeral service will be help at
        <funeral_place>Patna Kirk, Patna</funeral_place> on
        <funeral_date>Monday 26th June, 2017</funeral_date> at
        <funeral_time>11.00am</funeral_time> and thereafter to
        <cemetery_place>Patna Cemetery</cemetery_place> to which
        <guests_list>all friends</guests_list> are respectfully invited. Donations if desired to
        <charity_name>Cancer Research UK and Strathcarron Hospice</charity_name>.
    </funerla_component>
</obit>
```

Fig. 1: Problem-Side representation of an obituary

Hence, an obituary contains information, as attribute values, on the different people, relationships, places, organisations, etc involved, and can be used to build an effective case representation that will be helpful for identifying similar cases to new problems. Around 40 relevant attributes have been selected to represent an obituary as a case in the case-base, as shown in fig. 2 [4]. From the example obituary, we can see that the first sentence talks about the personal details of the deceased person, followed by relatives in second sentence and funeral information in the last sentence. This is a typical paragraph construction, so we can divide all the extracted obituaries into three components and annotate them with the identified attributes.

The attributes identified for annotations are set to be gender independent. For example, in fig. 1 we have taken "*mum*" as a value for attribute "*parent_gender*". That means, the deceased person was parent (in this case mother) to "*Jack*" ("*children_name*"). So if we have a target problem with "*parent_gender* $\rightarrow$ *father*", the case in fig. 1 can still be re-used as a possible solution. An initial case-base has been created to seed the system by manually annotating 100 samples.

[4] For the columns marked M/O: Mandatory/Optional, '-': Attribute value filled automatically

Attribute Name	Identifier Tag	Attribute Type	M/O	Comment
Name	< *name* >	String	M	
Gender	< *gender* >	Binary	M	Male (1) or Female (2)
Age	< *age* >	Number	O	Numbers in range 110
Demise Date	< *demise_date* >	Date	M	
Demise Place	< *demise_place* >	String	O	
Demise How	< *demise_how* >	3 Category	O	Peacefully (1), Suddenly (2), Peacefully but suddenly (3)
Demise Reason	< *demise_reason* >	Dropdown List	O	Name of any specific illness or accident
Home Town	< *home_town* >	String	O	Deceased Person Home Town
Nick Name	< *nick_name* >	String	O	
Occupation	< *occupation* >	String	O	Most recent job
Previous Works	< *previous_works* >	String	O	any previous achievements/-works

(a) Personal Information Component

Attribute Name	Identifier Tag	Att. Type	M/O	Comment
Spouse Name	< *spouse_name* >	String	M	
Spouse Gender	< *spouse_gender* >	Binary	-	Husband or Wife
Children Name	< *children_name* >	Array	O	
Parent Gender	< *parent_gender* >	String	-	Father or Mother
Grandchildren Name	< *grandchildren_name* >	Array	O	
Grandparent gender	< *grandparent_gender* >	String	-	Grandpa or Grandmother
Siblings Name	< *siblings_name* >	Array	O	
Siblings gender	< *siblings_gender* >	String	-	Brother or sister
Children-in-law Name	< *children_in_law_name* >	Array	O	
Parent-in-law gender	< *parent_in_law_gender* >	String	-	Father or Mother in law
Siblings-in-law Name	< *siblings_in_law_name* >	Array	O	
Siblings-in-law gender	< *siblings_in_law_gender* >	String	-	Brother or sister in law
Other Relations	< *other_relations_names* >	Array	O	
Friends Name	< *friends_name* >	Array	O	Name of the friends

(b) Relations Component

Attribute Name	Identifier Tag	Attribute Type	M/O	Comment
Funeral Place	< *funeral_place* >	String	M	
Funeral Date	< *funeral_date* >	Date	M	
Funeral Time	< *funeral_time* >	Time	M	
Cemetery Place	< *cemetery_place* >	String	O	
Cemetery Time	< *cemetery_time* >	Time	O	
Funeral Flowers	< *flowers* >	Binary	M	Family flowers only or welcome from all
Guests List	< *guests_list* >	Category	M	Public or private
Attire Request	< *funeral_attire* >	String	O	Any specific kind of attire
Donation	< *charity_name* >	String	O	Charity name for any donation
Associated Message	< *funeral_message* >	String	O	If the user wants to drop some message

(c) Funeral Component

Fig. 2: Attributes used for representation of obituaries.

4.2 Similarity Measure for Retrieval

In order to measure similarity between cases, we investigate two variants of Euclidean distance. The the first approach is straight-forward, where we match the number of features in the problem with number of features in the cases from the case-base. The first similarity measure (Measure 1) is shown in the algorithm 1.

There can be a problem with algorithm 1 where the target case has fewer features than the case form the case-base. Let's take an example where the target case has only 10 attributes out of a possible 40. In that scenario, cases with more than the 10 attributes will also have the same similarity score as cases with the exact 10 features. To counter this problem, we propose the new similarity measure (Measure 2) described in algorithm 2. Here we penalise the samples with extra attributes that can produce poor retrievals.

4.3 Text Reuse

In the previous section we observed that there can be problems in situations where there is a miss-alignment in the number of attribute values. We proposed

Algorithm 1 Similarity Measure 1

Input: Features List from the target case (L), List of feature lists from all the cases in case base (C)
Output: List of samples and their similarity score (O)

```
O = [ ]
for each sample in C do
    score = 0
    for each feature in sample do
        if feature in L then
            score += 1
        end if
    end for
    O.append(arg(sample), score)
end for
return O
```

Algorithm 2 Similarity Measure 2

Input: Features List from the target case (L), List of feature lists from all the cases in case base (C)
Output: List of samples and their similarity score (O)

```
O = [ ]
for each sample in C do
    score = 0
    for each feature in sample do
        if feature in L then
            score += 1
        else
            score -= 1
        end if
    end for
    O.append(arg(sample), score)
end for
return O
```

a new similarity measure to address this problem in algorithm 2. However, this method can also lead to a problem. The set of retrieved cases for a target problem with very less attributes might have same number of attributes but have different attribute types. For example, a target problem with only "*spouse name*" in "*relation section*" and "*funeral place/time*" in "*funeral section*" along with all the attributes from "*personal info section*", the retrieved cases might contain only "*name*" and "*home town*" of the deceased person along with all the attributes from "*funeral section*". In that way the number of attributes may be the same giving a high similarity score but in practice, the retrieved case is not a good example of a similar case for re-use.

To address this problem, we investigate an alternative case representation where the case-base is broken down into three components, namely: personal

Problem Side (*Attribute* → **Value**)	**Solution Side**
name → OLIVIA WILSON *demise_how* → Peacefully *demise_date* → 14th May 2019 *demise_place* → home *nick_name* → Olivia *home_town* → Patna *spouse_gender* → wife *spouse_name* → the late Robert James Wilson *parent_gender* → mum *children_name* → Jack *children_in_law_name* → Emily *grandparent_gender* → gran *grandchildren_name* → Ava, Lucy and Logan *other_relations_types* → aunt *siblings_gender* → sister *funeral_place* → Patna Kirk, Patna *funeral_date* → Monday 26th May, 2019 *funeral_time* → 11.00am *cemetery_place* → Patna Cemetery *guests_list* → all friends *charity_name* → Cancer Research UK and Strathcarron Hospice	OLIVIA WILSON, Peacefully on the 14th May 2019 at home, Olivia of Patna. Beloved wife to the late James Wilson, much loved mum to Jack and partner Emily, gran to Ava, Lucy and Logan, loving aunt, sister and a friend to all. Funeral service will be held at Patna Kirk, Patna on Monday 26th May, 2019 at 11.00am and thereafter to Patna Cemetery to which all friends are respectfully invited. Donations if desired to Cancer Research UK and Strathcarron Hospice.

(a) Basic

Component Name	**Problem Side** (*Attribute* → **Value**)	**Solution Side**
Personal Info	*name* → OLIVIA WILSON *demise_how* → Peacefully *demise_date* → 14th May 2019 *demise_place* → home *nick_name* → Olivia *home_town* → Patna	OLIVIA WILSON, Peacefully on the 14th May 2019 at home, Olivia of Patna.
Relations	*spouse_gender* → wife *spouse_name* → the late James Wilson *parent_gender* → mum *children_name* → Jack *children_in_law_name* → Emily *grandparent_gender* → gran *grandchildren_name* → Ava, Lucy and Logan *other_relations_types* → aunt *siblings_gender* → sister	Beloved wife to the late James Wilson, much loved mum to Jack and partner Emily, gran to Ava, Lucy and Logan, loving aunt, sister and a friend to all.
Funeral	*funeral_place* → Patna Kirk, Patna *funeral_date* → Monday 26th May, 2019 *funeral_time* → 11.00am *cemetery_place* → Patna Cemetery *guests_list* → all friends *charity_name* → Cancer Research UK and Strathcarron Hospice	Funeral service will be held at Patna Kirk, Patna on Monday 26th May, 2019 at 11.00am and thereafter to Patna Cemetery to which all friends are respectfully invited. Donations if desired to Cancer Research UK and Strathcarron Hospice.

(b) Component

Fig. 3: An example obituary represented for different retrieval method.

info component; relations component; and funeral component. In this way, we can leverage our data and so find good retrieval examples with fewer cases. It is also hoped this approach will help increase diversity among the retrieved set. With this representation for a target problem, the retrieval will take part in three components.

Thus, we have two alternative representations:

- **Basic**: representing whole obituary as a one entity; and
- **Component**: representing cases as 3 different components.

An example case with both problem and solution side for basic retrieval is shown in fig. 3a while same case for the component retrieval is shown in fig. 3b.

5 Experimental Evaluation

Evaluation of our TCBR system is a challenging task. It is difficult to automatically measure the effectiveness of a system due to the diversity found in the natural language output. Human evaluation is an alternative which, while effective is expensive and very time consuming. Traditional machine translation and summarising metrics such as BLEU [10] and ROUGE [7] scores are unlikely to work well because these metrics are based on the overlap of n-grams of the generated text with an original reference text and so only consider lexical similarity. Also, they require a lot of reference text to measure the quality of generation which is very costly to get. To overcome these challenges we propose a problem-solution alignment metric as an unsupervised evaluation measure.

5.1 Case Alignment

A key principle of CBR is that "*similar problems have similar solutions*". The extent to which this principle holds true can be assessed by measuring the alignment between the problem-side and solution-side space. It is surmised that a good system design will have better alignment [8]. In this evaluation, we employ a novel approach to measuring case alignment by using normalised discounted cumulative gain to assess the correlation between proble-side and solution-side nearest neighbours. If the alignment is good then for a given problem-solution pair, the k nearest cases on problem-side must be similar as the k nearest-cases on the solution side.

For a given case-base C containing all the cases $\{c_1, c_2, \cdots, c_n\}$. Cases in C consist of problem−solution pairs, such that $c_i = \{p_i, s_i\}$, where $p_i \in P$ (problem set) and $s_i \in S$ (solution set). A target problem t represented using the case knowledge, we will retrieve two lists pl & sl which are sorted in order to the most similar cases both from the problem (pl) and the solution (sl) set respectively. On the solution side, BERT [3] is used to encode the sentences and then cosine similarity [14] between the test sample and other samples is used to generate the ordered list of similar cases. For the problem side the ordered list is created using the retrieval methods discussed in section 4. Both the lists will have $n-1$ items, where n is the size of the case-base.

From the list pl, we shall create a new list of weighted scores for the problem-side. We call it problem list weighted or plw. The weighting is done as follows:

$$plw(i) = \begin{cases} (k+1) - i, & \text{if } i \leq k \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

where k is the number of neighbours considered for retrieval. Similarly the cases in sl are weighted according to their pl counter-part and creating a solution list weighted or slw.

For example, if we have 10 cases in the case-base and for a given case c_i, with $k = 3$ the sl and pl are as follows:

$$pl = [8, 5, 6, 1, 4, 2, 3, 7, 0]$$
$$sl = [5, 6, 2, 4, 3, 7, 8, 1, 0]$$

These are the indices of the cases from both the sets. According to the eq. (1), weighted lists plw and slw are given as follows:

$$plw = [4, 3, 2, 1, 1, 1, 1, 1, 1]$$
$$slw = [3, 2, 1, 1, 1, 1, 4, 1, 1]$$

For an ideal case, both of the list should have same ranking order as they are retrieved for the same case. To measure the alignment of the case t we can use the normalised discounted cumulative gain [15] using the following formula:

$$Align(t) = \frac{DCG_{slw}}{DCG_{plw}} \tag{2}$$

where, DCG is the discounted cumulative gain, calculated using:

$$DCG(l) = \sum_{i=1}^{p} \frac{l(i)}{\log_2(i+1)} \tag{3}$$

where, l is some weighted list (e.g., plw or slw) and p is the size of that list. The value of nDCG $\in (0, 1]$.

The alignment of whole case-base can be the average of nDCG score of all the cases in the case-base.

$$AlignScore(CB) = \sum_{i=1}^{n} \frac{nDCG_i}{n} \tag{4}$$

where, n is the size of case-base. For component retrieval method, the total alignment score would be the average of $AlignScore$ of all the components. In our experiments, we take the value of $k = 5$ because of the fact that we need to show 5 options of automatically generated obituaries to the user.

5.2 Other Evaluations

In addition to the case alignment, we use BLEU score and cosine similarity for the evaluation of our system. BLEU score counts the average of overlapped n-grams from generated text with the reference texts. Cosine similarity on other hand measures the cosine angle between the projection of vectors in multi-dimensional space. For the vector representation of a sentence, we used BERT encoder to produce a contextual embedding for each sentence.

5.3 Average Attribute Errors

We define a reference metric as the number of missed attributes in the generated text as one measure of the competence of the evaluation metrics. In our scenario, where the pre-defined attributes play an important role in the retrieval and reuse of cases, it is important to measure the inclusion of these attributes in the generated text. In the absence of a human evaluation, we employ **Average Attribute Error** as a crude surrogate for human feedback.

The average attribute error is defined as the average number of missed attributes from the top 5 generated texts from our system. Again, top 5 cases are chosen because of the fact that the system needs to provide 5 optional texts to the user for a given input.

Table 1: Nomenclature of different methods.

	Basic Reuse	Component Reuse
Similarity Measure 1	**BS1**	**CS1**
Similarity Measure 2	**BS2**	**CS2**

For a target problem t, if we have n number of attributes and the $G = \{g_1, \cdots, g_5\}$ is the set of top 5 generated texts from one of the methods defined in table 1. The average attribute error e would be:

$$e(t) = \frac{\sum_{i=1}^{5} ||(n - |g_i|)||}{5} \tag{5}$$

where, $|g_i|$ is the number of attributes included in the i^{th} generation. The average of total number of samples in a case-base will be the average attribute error for the case-base.

We measure the correlation between average attribute error and other three metrics to find out which evaluation metric aligns well with the reference error.

6 Results & Discussion

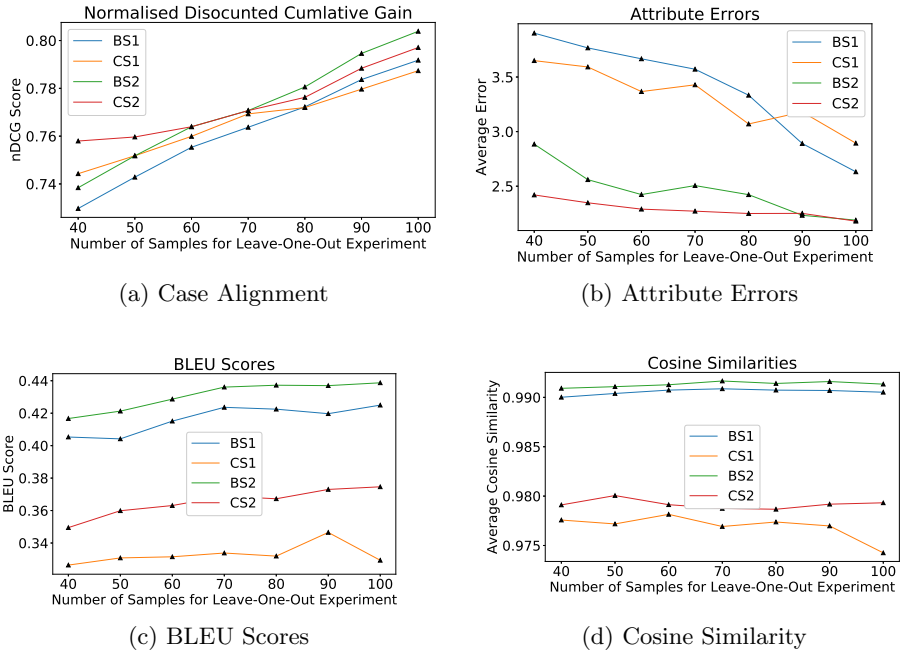
Our case-base contains 100 seed cases manually annotated to identify problem and solution components. We use a leave-one-out experiment for both representations described in section 4.3 (Basic and Component) with both similarity measures described in section 4.2 (Measure 1 and 2). Hence, We have four system combinations to evaluate as named in table 1.

6.1 Different Evaluations

The results from applying the 4 evaluation metrics to the retrieval sets obtained when employing the 4 system combinations are shown in fig. 4. We start our experiments with 40 cases initially, chosen to reflect the 40 attributes present in the problem representation. We repeat the experiments with increasing number of samples until we reach 100, i.e., the maximum number of seed cases available.

Case Alignment results are shown in fig. 4a, where we plot the change in case alignment score with respect to the number of cases used for experiment. For a given value on the x-axis, the corresponding value on the y-axis represent the average case alignment score of all the cases from the leave-one-out experiment. We can see that with the number of samples increasing, the case alignment is also improving. Which means with more data used for experiment we are continuing to achieve improved results and do not appear to have reached a plateau.

We can also observe that before 70 cases the alignment is better for *component retrieval* compared to *basic retrieval* while after 70 samples, the *basic retrieval* for both *similarity measures* gets better alignment than the *component retrieval*. This indicates that after sufficient case data is available there may be no need for



(a) Case Alignment

(b) Attribute Errors

(c) BLEU Scores

(d) Cosine Similarity

Fig. 4: Various results from leave-one-out-experiment

breaking down the obituary representation into several components because with more labelled cases diversity in the case base is increased allowing sufficiently similar cases to be found.

Results from the Average Attribute Error evaluation metric is shown in fig. 4b. Here we can see that with the change in number of cases used for experiment, the average count of missing attributes is reducing for all the four system combinations. Also, before 80 cases, the performance for *component* is better, while after 80 *basic* for both *similarity measures* gives improved results. This further supports the idea that with more cases available, there is no need to split obituaries into components.

In figs. 4c and 4d we show results for BLEU score and cosine similarity between the generated text and reference text. Both the metrics show little variations in score with respect to the change in number of cases available. The BLEU score for BS1 and BS2 is always around 0.40 to 0.44 while for CS1 and CS2 is 0.33 to 0.37. Similarly for cosine similarity, the average is almost 0.99 for BS1 and BS2 during all the number of samples while the score for CS1 and CS2 is around 0.975 go 0.98. This may be because these metrics only consider lexical similarity while ignoring the measure of attributes inclusion for generation.

Table 2: Pearson coefficient score for correlation

	Case Alignment	**BLEU Score**	**Cosine Similarity**
Pearson Score	-0.9238	-0.7019	-0.0296

6.2 Correlation of Metrics

We calculate the pearson correlation coefficient between average attribute error and the other three automated evaluation metrics which is shown in table 2. Here, we can observe that our proposed case alignment metric is highly correlated to the average attribute error. BLEU score is ranked second while the cosine similarity is third and is much less correlated. This demonstrates that our case alignment measure is an effective evaluation metric for the TCBR system.

7 Conclusion and Future Work

In this paper we presented a TCBR system developed for the automated generation of natural language obituaries from a large set of structured input attributes. The paper introduced two alternative case representation approaches, along with two different measures of similarity used for the retrieval of similar cases from the case-base.

The performance of our methods are evaluated using a novel unsupervised case alignment metric employing normalised discounted cumulative gain to compare problem-side and solution-side retrieval sets. Extensive experiments are conducted with an increasing number of seed cases available in a leave-one-out experiment. The proposed case alignment evaluation metric is compared with other commonly used supervised metrics as well as with average attribute error score, a simple surrogate for human feedback. The experiment results show that our unsupervised evaluation metric better correlates to the average attribute error compared to BLEU score and cosine similarity. Our evaluation metric is also domain independent and can be applied to different kinds of TCBR systems.

In future work for this project the intention is to measure and introduce more diversity into the set of generated obituaries and to automate the process of marking-up the data to ease the case-base creation process.

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