Summarisation of Electronic Health Records with Clinical Concept Guidance

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Abstract

Brief Hospital Course (BHC) summaries are succinct summaries of an entire hospital encounter, embedded within discharge summaries, written by senior clinicians responsible for the overall care of a patient. Methods to automatically produce summaries from inpatient documentation would be invaluable in reducing clinician manual burden of summarising documents under high time-pressure to admit and discharge patients. Automatically producing these summaries from the inpatient course, is a complex, multi-document summarisation task, as source notes are written from various perspectives (e.g. nursing, doctor, radiology), during the course of the hospitalisation. We demonstrate a range of methods for BHC summarisation demonstrating the performance of deep learning summarisation models across extractive and abstractive summarisation scenarios. We also test a novel ensemble extractive and abstractive summarisation model that incorporates a medical concept ontology (SNOMED) as a clinical guidance signal and shows superior performance in 2 real-world clinical data sets.

1 Introduction

A patient’s clinical journey is documented in rich free-text narratives stored in time-ordered linked documents in Electronic Health Records (EHRs). Narratives include commentary from multiple care teams, specialisms and perspectives with varying scope, detail, structure and time-span covered. Content broadly presents the patient experience, symptoms, findings and diagnosis alongside resulting procedures and interventions. Clinical and social histories and future prognoses are often referenced to provide further context and any potentially follow up actions to occur in some defined time period. Single notes also often mention or refer to previous notes. An encounter such as a simple routine outpatient procedure could generate only a few sentences, whereas a complex admission may result in hundreds of distinct documents. When a patient is discharged from an inpatient encounter, the discharging clinician summarises the entirety of the visit within a section of the Discharge Summary note known as the Brief Hospital Course (BHC).

Manually generating this summary is laborious, time-consuming and potentially error prone (O’Donnell et al., 2009). Fig. 1 shows a fictitious, multi-day inpatient encounter. This single admission produces 6 distinct documents from a range of perspectives (Nursing, Doctors, Radiology) in the first 18 hours. The first 2 Nursing - Progress Notes are by the same author, the differing radiology scans (X-ray vs. MRI) have different authors and the discharge summary is the same author that wrote the initial admission. Discharge occurs ∼2 days after admission with more notes taken than those shown. Each document can inform the BHC section. However, not all notes are treated equally, notes are categorised into care provider categories, and further by admission, progress, discharge amongst other types. Due to the volume of text and the time-constraints for doctors to produce these summaries, it is improbable that a clinician
author reads the entirety of the record and certainly not thoroughly.

In computational linguistics, this problem can be framed as a challenging multi-document summarisation task, with the model required to adapt to varying numbers of documents (simple vs complex cases), large time variances between notes, differences between note types, varying source document authors aims and focus areas.

A recent detailed analysis of BHC sections (Adams et al., 2021), found BHC summaries to: 1) be information dense, 2) switch quickly between extractive and abstractive summarisation styles, beginning with top-level extractive summaries of an admission followed by problem orientated abstractive summary of the admission, 3) be only a silver-standard and can lack important information.

To the authors knowledge, this is the first work to offer a range of summarisation models for BHC summarisation trained and tested on multiple real-world sources of clinical text. The contributions of this work are:

- A baseline evaluation of existing pre-trained Transformer models for abstractive summarisation fine-tuned on the BHC summarisation task.
- An evaluation of extractive top-k sentence extractive summarisation models. Using unsupervised and supervised methods to analyse the extractiveness of the opening BHC sentences.
- An adapted abstractive summarisation model (BART) (Lewis et al., 2020) to include a clinical ontology aware guidance signal of relevant terms to produce problem-list orientated abstractive summaries.
- An evaluation of an ensemble model for extractive and abstractive summarisation combining the extractive and abstractive models.

2 Background
2.1 Automatic Summarisation

Automatic summarisation of text aims to provide a concise, fluent representation of the source material, retaining ‘important’ information whilst ignoring redundant or irrelevant information. Formally, with single document summarisation, a set of documents \( T = \{t_1, t_2, \ldots, t_n\} \) we aim to find some function \( f(T) = T' \) where \( T' = \{t'_1, t'_2, \ldots, t'_m\} \) the set of texts that maximise some parameters of an effective summary. These parameters can include: maximum length that could vary according to use case, correctness if the generated summaries are factually inline with source texts, completeness, if the generated summary captures all important information from source texts, and fluency, a often subjective measure of the writing quality of the generated summary (Laban et al., 2020). In multi-document summarisation we have multiple texts for each sample \( T = \{t_{11}, t_{21}, \ldots, t_{n1, k}\} \). With BHC summarisation each \( t_i \) has one or more documents.

2.2 Extractive & Abstractive Summarisation

Research interest in automatic summarisation has a long history with empirical data-driven methods divisible into two main groups (Orăşan, 2019).

1. Extractive summarisation is the selection and combination of important words, phrases, or sentences i.e. some syntactic unit, of source texts to form the summary text. Consider some document \( t_i \) of syntactic units \( S_i = \{s_{1i}, s_{2i}, \cdots, s_{3i}\} \). \( f(t_i) = t'_i \) where \( t'_i = S' \) and \( S' \subseteq S_i \).

Some extractive summarisation methods can be considered Information Extraction (IE) (White et al., 2001) methods that identify important information and simply use \( s_j \) where the information is found, or possibly surrounding syntactic units \( s_{j-1} \) and \( s_{j+1} \). Information is extracted until desired summary length is reached or there is no more information to extract. Further extractive approaches search \( f \) rank a document’s \( S \) according to some importance metric and select the top-

2. Abstractive summarisation methods do not enforce generated summaries to be directly drawn from source texts. Instead, abstractive methods allow \( f \) to generate any syntactic unit, i.e. \( S' \not\subset S_i \). This means a ‘generation’ step is used once a latent importance model of source texts \( T \) is found. Models are often equipped with a suitable vocabulary \( V \) and are tasked with generating fluent, informative summary text, whilst being guided by the latent importance model.

Prior work has combined extractive and abstractive approaches, allowing \( f \) to balance abstractive
Recent large pre-trained Transformer(Vaswani et al., 2017) models have been shown to perform well across a range of tasks such as machine translation, question answering and abstractive summarisation(Raffel et al., 2020). The Transformer architecture supports learning of deep latent representations of input data by layering encoder and decoder blocks, the model learns deep contextual representations of input, and how to decode these representations for a range of sequence-to-sequence tasks.

2.3 Clinical Text Summarisation

Clinical narratives are estimated to comprise 80% of EHR data(Murdoch and Detsky, 2013). However, the development and application of text summarisation methods is progressing slowly(Mishra et al., 2014) when compared with areas such as disease prediction(Wynants et al., 2020), mortality prediction(Johnson et al., 2017), and clinical information extraction(Kreimeyer et al., 2017). Contributing factors include: 1) the difficulty in collecting reference summaries(Adams et al., 2021), Gold standard reference summary collection is difficult as the language is complex and highly specialised, 2) produced summaries present a high stakes AI scenario that has potential to cause negative downstream effects(Sambasivan et al., 2021) if the model makes errors, 3) assessing summarisation model performance using automated metrics such as ROUGE(Lin, 2004) is difficult, as high scoring models can still perform poorly when assessed by human evaluators(Sai et al., 2020).

Prior work has initially focused on extractive approaches(Moen et al., 2016). Approaches focused on modelling semantic similarity, and methods to optimally pick representative sentences, i.e. $s_i$ units, from latent topics discovered during model fitting. Recent work, has focused on single document summarisation of radiology reports(Zhang et al., 2018; Kondadadi et al., 2021; Dai et al., 2021). Radiology reports generally consist of three sections, the background of patient, the findings - the visible phenomena within the scan and finally the impression - an often abstractive summary of the background and findings used during the clinical followup. The impression sections are treated as the target reference summaries for model development. Radiology report summarisation is similar to a single document open-domain task, where modelling sentence salience and sentence compression are the primary aims.

2.4 BHC Summarisation

All admissions will have a discharge summary containing a BHC section. Prior work(Adams et al., 2021) has shown BHC sections are: 1) dense with clinical terms, 2) can widely vary in complexity, 3) quickly switch between extractive and abstractive styles and 4) reference summary quality can be low. These make the BHC summarisation task a difficult task. We address these problems with our proposed methods and experimental setup.

3 Datasets & Methods

3.1 Datasets

We extensively pre-process and clean the admission’s discharge summaries to extract only the BHC section. We discard the rest of the discharge summary so as to not bias the source texts. Our datasets are:

- **MIMIC-III**: (Johnson et al., 2016) A large, US based ICU dataset collected between 2001-2012 containing 53,423 distinct admissions. We extract BHC sections from discharge summaries with regular expressions and clean all other notes of headers / footers resulting in 1,441,109 unique documents.

- **KCH**: clinical records for inpatients diagnosed with cerebral infarction (ICD10 code:I63.*) from the King’s College Hospital (KCH) NHS Foundation Trust, London, UK, EHR. We extract data via the Trust deployed CogStack(Jackson et al., 2018) system, an Elasticsearch based ingestion and harmonization pipeline for EHR data. We extract BHC sections with regular expressions and clean source notes of common headers / footers resulting in 34,179 unique documents.

Table 1 shows that the average case includes many documents, over a multi-day stay. The MIMIC-III dataset of USA based ICU admissions, are skewed towards complex multi-day stays generating many small EHR notes. The KCH dataset are UK-derived clinical records containing only patients diagnosed with cerebral infarction requiring inpatient rehabilitation for associated disability and therefore covers substantially longer time periods.

Concatenating entire patient episode free-text narratives can create very long sequences of text.
Table 1: Descriptive statistics for our MIMIC-III (M-III) and KCH clinical text data. From left to right, the number of admissions, the average admission length in days, the average number of notes per admission, the average sequence length of a document excl. the discharge summary, and the average sequence length of the BHC section within the the discharge summary.

| Dataset | # Adm | Adm Length | # Docs | Src Seq | BHC Seq |
|---------|-------|------------|--------|---------|---------|
| M-III   | 47,591| 7          | 206    | 731     |         |
| KCH     | 1,586 | 49         | 441    | 274     |         |

For encounters that are over 1000 sentences we pick the top and bottom 500 sentences, based on the intuition that patient notes often begin with an important admission note describing the patient history, initial diagnosis and finish with the most recent summary of the patient state. Our source-code for cleaning and preparing the data, and the following model code is made available to the research community¹.

### 3.2 Extractive Baseline BHC Approaches

Our initial experiments test a recent finding that BHC sections are often extractive summaries initially before moving to more abstractive summaries as the BHC section progresses². We compare a range of unsupervised and supervised extractive summarisation models to predict the initial sentences of the BHC sections.

Fig. 2, shows our baseline extractive model architectures. All methods first concatenate each document text in chronological order, split into sentences via Spacy², then embed sentences by averaging GloVe³⁴⁵ or directly using S-BERT⁶ embeddings, finally feeding these to a ranking model, an unsupervised TextRank⁷ or supervised Bi-LSTM⁸ model. We train multiple models to select top 1 to 15 ranked sentences. The Oracle model uses the target output summary directly to rank source sentences using Gestalt Pattern matching⁹ to compute the ratio of the matching sub-sequences of ‘tokens’, (i.e. white-space separated words), of target sentences with all other source sentences. The Oracle model provides an estimate of the performance ceiling of sentence based extractive summarisation for both datasets.

### 3.3 Pre-Trained Transformer Based Models

We consider end-to-end abstractive summarisation models as further baselines. Large pre-trained Transformer models have been successful across a variety of tasks including textual summarisation. Models such as BERT⁸, T5⁹ and BART⁵ have demonstrated state-of-the-art performance across classification, summarisation, translation, language comprehension and question answering with for the most part a single model architecture. Transformer models for sequence-to-sequence (seq2seq) tasks such as machine translation and summarisation consist of layers of Transformer blocks configured either as encoders or decoders. Models such as T5 and BART are end-to-end trained for a range of tasks, whereas BERT in its original configuration consisted of encoder only Transformer blocks. Further work has showed BERT models can be repurposed in encoder-decoder configurations for summarisation.

Once trained on large, open-domain datasets these models can be re-used on further specialised domains, transferring base knowledge to a narrower domain and problem. Transfer learning has recently been shown to be effective for biomedical use cases. However, to our knowledge BHC summarisation has not been

¹https://github.com/tomolopolis/BHC-Summarisation
²https://spacy.io/
considered to date, and our baseline experiments initially establish if large pre-trained models can be fine-tuned to produce high quality BHC sections from source notes directly.

All abstractive models have been pre-trained on large corpora of open-domain text prior to fine-tuning with clinical text. We use existing pre-trained model parameter and configurations from the publicly available huggingface model hub\(^3\). Fine-tuning is performed using 3 Nvidia Titan X GPUs (M-III experiments) or Nvidia DGX 8 V100 GPUs (KCH experiments). We split datasets 80/10/10 for training, validation and test. We report results on test only.

As discussed in Section 3.1 clinical notes and BHC sections are highly variable in length and complexity. One limitation of recent models are the limited source and target text sequence lengths that can be produced due to the self-attention mechanism requiring all input representations to attend to all others. For example, BERT scales quadratically limiting the max input sequence length to 512. BHC summarisation is difficult as both input source notes are (far) greater than this maximum, as shown in Table 1. Recent models such as the Reformer(Kitaev et al., 2020), and LongFormer(Beltagy et al., 2020) use various optimisations for the attention calculations to enable longer sequences to be encoded / decoded.

Abstractive summarisation models use source text saliency to focus the summary on only the important parts of the source text. Models must also learn how to faithfully produce source texts alongside ensuring the correct content. Prior work has shown models can be prone to ‘hallucinations’, producing text that is not representative of the source text(Zhao et al., 2020). This is problematic for high risk settings such as healthcare but to our knowledge this problem has only been studied for radiology report summarisation(Zhang et al., 2020b).

| Table 2 shows descriptive statistics of the extracted terms of both datasets. The ‘term density’ is average number of word tokens for each concept extracted. We observe that for MIMIC-III and KCH datasets the Notes and BHC sections have similar SNOMED-CT term density, 56 / 52 and 26 / 29 token densities respectively, but when considering unique terms the BHC sections have almost double the density of unique clinical terms (63 Notes vs 118 BHC) for M-III whereas for the KCH notes it is circa equivalent (at 35 Notes vs 32 BHC), indicating in the M-III dataset BHC sections quickly change from one clinical topic to another when compared to source notes. Redundancy within these datasets have been described in prior work(Searle et al., 2021).

We use the huggingface\(^4\) BART(Lewis et al., 2020) architecture pretrained on open-domain texts and additionally pretrained on a summarisation corpus PubMed(Gupta et al., 2021). We choose this architecture as it is specifically tuned for natural language generation (NLG) including summarisation. We follow the architecture modifications outlined in recent work(Dou et al., 2021). This includes using dual Transformer encoder stacks for text and guidance input, namely the MedCAT extracted concept sequences. Parameters are shared for the first 3 encoder stacks reducing number of model parameters. The rest of the encoder Transformer blocks are specific to either the original text input or the as-

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\(^3\)https://huggingface.co/models

\(^4\)https://huggingface.co/
Table 2: Extracted and linked average: term counts, unique term counts, and their respective densities with regards to the number tokens per clinical term.

|       | Dataset | M-III | KCH |
|-------|---------|-------|-----|
| Notes | # Terms | 156   | 110 |
|       | Term Density | 55   | 26  |
|       | # Uniq Terms | 56   | 43  |
|       | Uniq Term Density | 118 | 32  |
| BHC   | # Terms | 19    | 10  |
|       | Term Density | 52   | 29  |
|       | # Uniq Terms | 15   | 8   |
|       | Uniq Term Density | 63  | 35  |

Table 4 shows our pre-trained Transformer based models fine-tuned on our datasets. We observe that the performance of these deep pre-trained models is not comparable with open-domain summarisation, even when these models are further pre-trained on biomedical corpora such as PubMed or even MIMIC-III itself. Prior work reports ROUGE-L F1 scores between 37-41 points for BART, BERT, T5 with the open domain summarisation datasets, indicates the guidance signal choice can affect the resulting summary performance (Dou et al., 2021).

Our final experiments ensemble the above clinically guided abstractive model with our extractive top-level summary models, therefore utilising both the extractive and abstractive models simultaneously. We predict the initial n lines of the BHC section using the extractive model then use the abstractive model with the guidance signal to predict the following detailed section.

4 Results

4.1 Extractive Models

Our extractive models rank all sentences within the source text to find the top-k salient sentences that comprise the summary. Table 3 show our results across varying initial BHC section sentence limits for the various model embedding and ranking model configurations. Our results support prior work (Adams et al., 2021) that found BHC sections are initially extractive then quickly move to abstractive problem focused narratives. The Oracle model that has access to the target BHC section to rank candidate sentences against, shows the performance ceiling on both datasets is between 5 and 10 of the initial BHC sentences. This is more clearly shown in the KCH dataset with only a very small improvement between 5 and 15 sentences.

Our best performing ranker models use the semantic contextual sentence embeddings from S-BERT and the LSTM ranker across the majority of the sentence limits for both datasets. It is noteworthy that the improvements of using sentence specific embeddings S-BERT vs average word vectors are minor in comparison to performance improvements from the unsupervised TextRank ranker to the supervised LSTM model. This suggests that relying on relative importance of words and sentences within the documents is an ineffective model, and domain knowledge is needed to build BHCs.

4.2 Abstractive Models

Figure 3: The Encoder-Decoder Architecture using Clinical relevant guidance signal during the encoding, decoding process.
Table 3: ROUGE-LSum F1 scores for the extractive summarisation via sentence ranking for varying sentence limits. **Bold** indicates the best score across each sentence limit experiment. The Oracle model results are the performance ceiling for each configuration.

| Sentence Limit | MIMIC-III | KCH |
|----------------|-----------|-----|
|                | TextRank | Bi-LSTM | Oracle | TextRank | Bi-LSTM | Oracle |
| 1              | 0.0       | 0.0     | 18.3   | 21.8     | 30.2       | 14.7   | 23.3 |
| 2              | 5.6       | 5.0     | 17.2   | 18.8     | 31.1       | 8.3    | 29.1 |
| 3              | 7.6       | 5.1     | 16.6   | 17.5     | 31.8       | 10.8   | 31.7 |
| 5              | 18.8      | 11.3    | 22.1   | **23.5** | 32.8       | 12.4   | 34.2 |
| 10             | 17.9      | 17.7    | 27.5   | **28.7** | 34.3       | 13.4   | 20.59 |
| 15             | 24.1      | 28.3    | 30.1   | **31.1** | 35.3       | 15.8   | 16.0 |

Table 4: ROUGE-LSum and ROUGE-2 F1 scores for pre-trained transformer models fine-tuned on the entirety of the BHC Summarisation task.

| Model | M-III | KCH |
|-------|-------|-----|
| T5-base | 7.3 / 1.3 | 11.0 / 6.3 |
| T5-small | 14.4 / 5.6 | 10.8 / 4.1 |
| BERT-2-BERT | 22.4 / 4.6 | 7.4 / 2.1 |
| BERT-2-BERT (PubMed) | 23.8 / 4.2 | 6.2 / 1.6 |
| BERT-2-BERT (M-III) | - | 8.6 / 2.2 |
| BART | **26.9** / **11.1** | 17.1 / 8.0 |
| BART (PubMed) | **32.7** / **11.1** | **22.1** / **8.6** |

Table 5: ROUGE-LSum / ROUGE-2 F1 scores for our clinically guided abstractive summarisation models. BART is pre-trained on the open-domain XSUM(Narayan et al., 2018) datasets, and BART (PM) is pre-trained on PubMed(Gupta et al., 2021). **Bold** indicates the best performance for the metric and dataset.

| Model | M-III | KCH |
|-------|-------|-----|
| BART | 26.9 / 11.1 | 17.1 / 8.0 |
| BART + Prb | 26.0 / 9.1 | 23.4 / 12.0 |
| BART + (Prb & Inv) | 26.2 / 8.5 | 23.4 / 12.2 |
| BART(PM) | 32.7 / 11.1 | 22.1 / 8.6 |
| BART(PM) + Prb | **34.7** / **10.6** | **26.6** / **13.7** |
| BART(PM) + (Prb & Inv) | 33.6 / 11.5 | 24.0 / 12.8 |

Table 5 shows our guidance aware abstractive summarisation results. We use 2 different guidance signals extracted by our pretrained MedCAT model. The first signal Prb includes only the problem extracted concepts. The second Prb + Inv includes MedCAT extracted problems and interventions.

4.3 Clinically Guided Abstractive Summarisation

Table 5 shows our guidance aware abstractive summarisation results. We use 2 different guidance signals extracted by our pretrained MedCAT model. The first signal Prb includes only the problem extracted concepts. The second Prb + Inv includes MedCAT extracted problems and interventions.

The M-III BART shows a small drop in performance, 1 and 3 points with both guidance signals, whereas the KCH model improves by 6 and 4 points for ROUGE-LSum and ROUGE-2 respectively. For BART(PubMed) we observe improved ROUGE-LSum performance with both guidance signal types Prb and Prb + Inv. We observe a small gain with ROUGE-2 in MIMIC-III but more noticeable in KCH( 4 points). BART(PubMed) experiments show both guidance signals are comparable, with Prb offering a marginal improvements when compared to the Prb + Inv signal, despite there being less guidance offered.

4.4 Ensemble Extractive / Abstractive Summarisation

Table 6 shows ablation results for our baseline and ensemble models. Abs is the abstractive only model BART with PubMed pre-training. Ext + Abs is the extractive and abstractive model - S-BERT into Bi-
Table 6: ROUGE-LSum and ROUGE-2 F1 score results for our baseline abstractive and ensemble summariser configurations. Bold indicates the best performance for the respective metric / dataset pair.

| Model      | M-III | KCH |
|------------|-------|-----|
| Abs        | 32.7  | 11.1| 22.1 / 8.6 |
| Ext + Abs  | 34.9  | 10.6| 23.6 / 7.5 |
| Ext + Abs + G | 34.9 | 10.6| 22.4 / 6.7 |

Table 7: MedCAT Extracted Term comparisons vs reference summary. Average % of problem only, intervention only and both problem & intervention terms in the generated vs the reference summary. Bold indicates model with highest proportion of clinical terms generated compared with reference summary.

| Dataset | Model          | % Prob | % Inv | % Total |
|---------|----------------|--------|-------|---------|
| M-III   | Abs            | 31     | 32    | 34      |
|         | Ext + Abs      | 33     | 33    | 34      |
|         | Ext + Abs + G  | 35     | 35    | 34      |
| CG      | Abs            | 40     | 30    | 38      |
|         | Ext + Abs      | 41     | 34    | 41      |
|         | Ext + Abs + G  | 43     | 34    | 42      |

4.5 Summarisation Extracted Concept Analysis

Alongside ROUGE scores, we analyse the clinical terms output by our summarisation models. As our guidance signal should push the model to generate more clinically relevant information. We run our pre-trained NER+L model (MedCAT), the same model used to produce the guidance signals, over the generated summaries in from models in Table 6 comparing the terms present in the reference summary and the proportion our generated summaries capture.

Table 7 shows the proportion of concepts that we successfully generate in the predicted summaries vs the reference summaries. There is a small improvement with both datasets using the guidance model, indicating the guidance signal is assisting the model produce more clinically relevant terms. The guidance assists the generation of problems more so than interventions unsurprisingly as this guidance only includes problem extracted terms. Overall, there is clearly still a majority of concepts (>50%) that are missed entirely by all generated summaries, suggesting there is plenty of room for improvement.

4.6 Qualitative Analysis

We manually review 20 random summaries from the set of model configurations presented in Table 5 and 6. We compare the generated BHC with the reference summary and the original source notes. We note that the abstractive models generate coherent and fluent text 70% of the time with the other 30% degrading into poor performing text with repeated phrases or words within and across sentences - a common problem in abstractive summarisation tasks, especially as the model is auto-regressive and conditioned on prior generated tokens.

During manual review we were surprised sometimes at the large differences in abstractive vs abstractive with guidance, as their ROUGE and MedCAT extracted concept proportion scores were so similar. From our random sample, we saw our guidance model often produced far longer summaries than the baseline abstractive model.

We notice that our ensembling strategy to first sample extractive sentences then from the abstractive model do not read coherently. This indicates that summaries move between extractive and abstractive generation at the sub-sentence level, and require a more sophisticated model to balance extractive selection of representative words or phrases alongside abstractive generation, e.g. the Pointer Generator model(See et al., 2017).

5 Discussion and Future Work

Our sentence ranking extractive summarisation experiments suggest the amount of 'extractiveness' for a BHC section depends largely on the dataset. The M-III dataset is more consistently 'extractive' than KCH, as seen by the differences in Oracle model performance as the sentence limit increases. Our best performing model uses a pre-trained contextual sentence embedding model (SBERT) alongside a Bi-LSTM. Future work could consider further ranking models i.e. a Transformer model to rank sentences, or an appropriate embedding boundary to build sub-sentence, or phrase
level embeddings extractive summaries from these. Our fine-tuning of pre-trained abstractive summarisation systems suggest BART, the only model specifically trained for NLG tasks such as summarisation, offers the best performance across datasets and metrics for BHC summarisation. Models such as T5, a general seq-to-seq Transformer model and the BERT-2-BERT models perform substantially worse than BART. For BART we find that further pre-training on a relevant corpus i.e. PubMed(Gupta et al., 2021) compared to only open-domain pre-training, offers improvements inline with prior research(Rogers et al., 2020).

We find that guidance signals for BHC abstractive summarisation offers improvements compared to our best model without guidance. We observe best performance once an existing pre-trained model has already been fine-tuned with biomedical data. We observe that guidance signal improvements are dataset dependent. All experiments use the equivalent hyperparameters, e.g. learning rate, learning rate scheduler, epoch number etc. as the baseline abstractive models. It is likely that further performance gains are possible with systematic hyperparameter tuning. The guidance models share the parameters for the initial 3 encoder layers. Further work could explore the effect of increasing or decreasing the number of shared parameters.

5.1 Guidance Signal

The guidance signal uses a pre-trained MedCAT(Kraljevic et al., 2021) model. This model has not been validated across the entirety of clinical terms that could be extracted. It has been configured to favour precision over recall, and so likely misses clinical terms that otherwise should be identified and included within the guidance signal. Further work could fine-tune and improve the model performance to improve the guidance signal offered to the summarisation model using the MedCAT annotation tool and workflow(Searle et al., 2019).

For successful model fine-tuning the guidance signal must be aligned with the raw text input. We align the signal by padding the signal with the white space token, but further experiments could investigate aligning the signal with syntactic hints such as punctuation, i.e. full stops, commas, new lines, colons etc. Further work could also experiment with replacing identified guidance terms directly with clinical concept embeddings. During our experiments we attempted to replace the raw text with the standardised terminology name but only keeping the recognised source value from the text for model convergence.

5.2 Ensemble Models

We use a very simple ensembling strategy, sampling the extractive model and feeding into the abstractive summariser. Prior work suggests that BHC sections are initially extractive then become abstractive(Adams et al., 2021). We find this to be partly true - we reach an Oracle performance limit for both datasets between 10 and 15 sentences - but it is probably at the sub-sentence / phrase level rather than full sentences where summaries are extractive. Further work could explore a PG(See et al., 2017) network architecture, with a mechanism to favour extractiveness initially then abstractive generation afterwards.

5.3 Problems with Abstractive Summarisation Models

Repetition is a known problem with Abstractive summarisation models(Nair et al., 2021). Prior work have studied numerous methods to reduce repetition and therefore improve summarisation quality. These include a specific training regime that improves the models ability to sample previously unselected n-grams(Welleck et al., 2020), and a coverage model that adjusts the loss to include words and phrases that sufficiently cover the source text(See et al., 2017). Repetition is highly unlikely to occur in human generated summaries. Utilising the above techniques would likely improve performance, as observed in open-domain settings(Nair et al., 2021), although we argue this would still not guide the model to ‘focus’ on the problem-list during summary generation as our method allows.

Factual correctness is an important problem in summarisation and especially important applying these models to clinical scenarios, a high stakes use case that lead to large downstream impacts for model errors. An incorrect statement within a generated BHC summary could miss a diagnosis, follow-up or report a result incorrectly. A real deployment of a BHC summarisation system would likely require a ‘human-in-the-loop’ to monitor, similar to most medical AI(Jotterand and Bosco, 2020). The human user would correct, further edit and sign-off on any produced summaries. Even if a system were only able to provide a basic BHC summary, this would still beneficially reduce the
administrative burden of completing the BHC section from scratch.

5.4 Reference Summary Quality

The reference summary BHC sections in both datasets were collected as part of routine care. They have not been reviewed and validated so represent a silver-standard BHCs. Real-world clinical data often does not undergo secondary validation, and even MIMIC-III a heavily studied clinical dataset has data quality concerns (Searle et al., 2020; Afshar et al., 2021). Finally, we argue in line with prior analysis that BHC writing is context and author specific so it is likely another domain expert clinician with different training, locale etc. would result in a different summary (Adams et al., 2021).

More analysis should be performed to understand the gap in performance between generated and reference BHC summaries by using ROUGE, or proportions of extracted clinical terms as the reference summary might include bias or subjective inclusions / exclusions of material from the source notes.

5.5 Summarisation Metrics

The ROUGE score shows our guidance assisted and ensemble models offer some but limited improvement. However, in context current top performing ROUGE-LSum scores in open-domain summarisation are at 37-41 points (Lewis et al., 2020) and improvements needed for achieving a few points above the current state-of-the-art is generally non-linear. Analysis using MedCAT extracted concepts and from manual review indicates the addition of guidance helps to produce longer more ‘clinically complete’ summaries despite the similarity in ROUGE score.

ROUGE has been criticised in the literature as summarisation quality can score highly whilst perform poorly during manual evaluation (Schluter, 2017). Alternative metrics such as BERTScore (Zhang et al., 2020a) or the recently introduced question answering metrics (Eyal et al., 2019; Wang et al., 2020) rely on manually generating questions for reference/generated summary pairs or a pre-trained answer conditional question generation model. Assessing our experimental scenarios with these metrics is left to future work, but would likely assist in higher quality, more factually correct summaries. Factual accuracy is critical in BHC generation, as this section is both a legal record and likely to be used by followup care upon discharge.

5.6 Downstream Summary Use

Automatic generation of BHC sections from source notes is still a long way off. Embedding an automatic summarisation model in high stakes scenarios such as healthcare would involve engineering a solution well beyond any research project. Aside from initial validation, ML operations tasks such as detecting model drift or bias would be essential.

In any real-use scenario - a generated summary would likely only be used with explicit supervision and ultimate responsibility for the produced summary, ensuring factual correctness and coherence. (Pivovarov and Elhadad, 2015) provides a further categorization of generated summaries and how the output is integrated into a workflow. They explain that indicative summaries highlight significant or important parts of source texts, whereas informative summaries are intended to replace the original text and used in place of it.

6 Conclusions

Our work has demonstrated a range of possible models using both extractive, abstractive summarisation approaches, pre-trained and fine-tuned to specific data and a pre-trained guidance signal generation model (MedCAT) to push the summarisation models to focus on clinically relevant terms. We train a state-of-the-art abstractive model guided by clinically relevant problem terms outperforming all baselines across 2 real-world clinical dataset.

Overall, we have shown BHC automated summarisation to be a challenging task supporting prior work (Adams et al., 2021) suggesting that BHCs are both extractive and abstractive. We hope this work motivates further work in this area that could one day improve the overall healthcare experience for patient and clinician alike through the minimisation of screen time. A well documented contributing factor for clinician burn-out (McPeek-Hinz et al., 2021; O’Donnell et al., 2009).

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We configure MedCAT (Kraljevic et al., 2021) to extract ‘problem’ and intervention terms. Table 8 and 9 are provided.

**B Extractive Summarisation Plots**

**Precision, Recall, F1 Plots Appendix**

Extractive Summarisation Methods for Top-N-Line BHC Summarisation
| Type ID | SCTID  | Root Term            | Description        | # Concepts Available |
|---------|--------|----------------------|--------------------|----------------------|
| T-11    | 64572001 | Disorder            |                    | 77,284               |
| T-18    | 404684003 | Clinical Finding    |                    | 44,201               |
| T-29    | 49755003  | Morphologic Abnormality |                | 4,897                |
| T-35    | 410607006 | Organism            |                    | 34,778               |
| T-38    | 260787004 | Physical Object     |                    | 198,890              |

Table 8: The set of ‘Problem’ semantic tags from SNOMED-CT configured within MedCAT, and extracted from source texts and BHC summaries

| Type ID | SCTID  | Root Term            | Description        | # Concepts Available |
|---------|--------|----------------------|--------------------|----------------------|
| T-9     | 373873005 | Clinical Drug      |                    | 6,247                |
| T-26    | 373873005 | Medicinal Product  |                    | 7,715                |
| T-27    | 373873005 | Medicinal Product Form |                | 6,203                |
| T-39    | 71388002  | Procedure           |                    | 6,4291               |
| T-40    | 373873005 | Product             |                    | 17,3894              |
| T-55    | 105590001 | Substance           |                    | 27,626               |

Table 9: The set of ‘Intervention’ semantic tags from SNOMED-CT configured within MedCAT. All SNOMED-CT terms with these semantic terms are extracted from source texts and BHC summaries and treated as ‘Intervention’ terms.

![Figure 4: Extractive score max](image)

![Figure 5: GloVe Embeddings: TextRank](image)
Figure 6: S-BERT embeddings: TextRank

Figure 7: S-BERT embeddings: Bi-LSTM