WHOSe Heritage: Classification of UNESCO World Heritage “Outstanding Universal Value” Documents with Smoothed Labels

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Abstract

The UNESCO World Heritage List (WHL) is to identify the exceptionally valuable cultural and natural heritage to be preserved for mankind as a whole. Evaluating and justifying the Outstanding Universal Value (OUV) of each nomination in WHL is essentially important for a property to be inscribed, and yet a complex task even for experts since the criteria are not mutually exclusive. Furthermore, manual annotation of heritage values, which is currently dominant in the field, is knowledge-demanding and time-consuming, impeding systematic analysis of such authoritative documents in terms of their implications on heritage management. This study applies state-of-the-art NLP models to build a classifier on a new real-world dataset containing official OUV justification statements, seeking an explainable, scalable, and less biased automation tool to facilitate the nomination, evaluation, and monitoring processes of World Heritage properties. Label smoothing is innovatively adapted to transform the task smoothly between multi-class and multi-label classification by adding prior inter-class relationship knowledge into the labels, improving the performance of most baselines. The study shows that the best models fine-tuned from BERT and ULMFit can reach 94.3% top-3 accuracy, which is promising to be further developed and applied in heritage research and practice.

1 Introduction

Since the World Heritage Convention was passed in 1972, a total of 1121 properties has been inscribed worldwide in the World Heritage List (WHL) up to 2019, aiming at a collective protection of the cultural and natural heritage of Outstanding Universal Value (OUV) for mankind as a whole (UNESCO, 1972; von Droste, 2011; Pereira Roders and van Oers, 2011). First proposed in 1976, OUV, meaning the “cultural and/or natural significance which is so exceptional as to transcend national boundaries and to be of common importance for present and future generations of all humanity”, has become the administrative requirement for any property to be nominated and inscribed into the WHL since 2005 (UNESCO, 2008; Jokilehto, 2006, 2008). All nominations to be included in WHL must meet one or more of the ten OUV criteria (6 for culture and 4 for nature), focusing on different aspects of cultural and natural heritage values. For example, Venice and its Lagoon¹ fulfills all six cultural criteria, while Sydney Opera House² only indicates criterion (i), which stresses that it represents a masterpiece of human creative genius.

However, the identification and evaluation of the OUV is a complex process that “can only be made through systematic thematic studies based on scientific research”, which heavily depends on expert knowledge in local and global levels, the time allowed for which also usually remains very limited (Jokilehto, 2008). Furthermore, the OUV criteria evaluation for the World Heritage (WH) properties can be ambiguous in the sense that: 1) the criteria are not mutually exclusive and contain common information about historic and aesthetic/artistic values as an integral part; 2) the State Parties, the ICOMOS Advisory Board, and the World Heritage Committee, which are the key actors to evaluate the OUV for a nomination, occasionally disagree with each other, though all are considered to be the experts in the domain (Jokilehto, 2008; Tarrafa Silva and Pereira Roders, 2010; von Droste, 2011). A thorough understanding of the intrinsic meaning of the OUV criteria pertaining to their semantic nuance and association is therefore needed to facilitate the future WHL inscription process.

¹http://whc.unesco.org/en/list/394
²http://whc.unesco.org/en/list/103
Meanwhile, the new direction of World Heritage management, supported by the Recommendation of Historic Urban Landscape and shown in the most recent OurWorldHeritage campaign\(^3\), boldly stresses the importance of social inclusion and the impact of the whole society on evaluating heritage values (UNESCO, 2011; Bandarin and van Oers, 2012). The traditional method of annotating heritage values and attributes manually by experts can be extremely time-consuming, knowledge-demanding, and sometimes biased by the experts’ prior knowledge, yet it is still dominantly applied in practice (Tarrafa Silva and Pereira Roders, 2012; Abdel Tawab, 2019; Tarrafa Silva and Pereira Roders, 2010). As such, it is difficult to scale up the analysis of heritage values and thus benefit from the massive official and/or user-generated content made by various stakeholders worldwide (Ginzarly et al., 2019).

A computational tool that can automate the heritage value identification could strongly enable authorities to study the effect of policies before implementation and stimulate the social inclusion in heritage management. Both needs point to NLP as a solution, since: 1) NLP models, especially in the deep learning era, are built and trained from data as a bottom-up approach, giving chances for models to investigate the existing OUV document and induce the intrinsic associations among the written justification statements and the corresponding OUV criteria, which is a supplement to the current top-down process, yielding a new perspective on interpreting the WHL; 2) with the idea of transfer learning, the general language models pretrained on massive corpus and fine-tuned on domain-specific data are typically good at scaling up and generalizing to broader tasks, creating chances to further apply the trained OUV classifier on social media posts and policy documents which do not necessarily have an identical distribution with the training data (Eisenstein, 2018; Rao and McMahan, 2019; Jurafsky and Martin, 2020).

Therefore, this study aims at training an explainable, scalable, and less-biased classifier which can reveal the intrinsic associations of World Heritage OUV criteria. The classifier should have a reasonable performance, generalizability, resource utilization, and inference efficiency, making it feasible to apply in real-world analyses by researchers and practitioners. As outcome, this paper presents the classifier of UNESCO World Heritage OUV with Smoothed Labels (WHOSe Heritage).

The contributions of this Paper can be summarized as follows: 1) A novel text classification dataset is presented, concerning a domain-specific task about Outstanding Universal Value for UNESCO World Heritage properties; the dataset is formulated such that it contains characteristics of both multi-class and multi-label classification; 2) Label smoothing technique is innovatively applied in the specific context to introduce the prior knowledge of label association into training, which turned out to be an effective way to improve performance in most investigated popular models as baselines; 3) Several deep-learning-based classifiers are trained and compared with some initial explorations on their explainability and generalizability, which can later benefit researchers and practitioners in real-world practice of heritage management, either during inscription process of new World Heritage properties or during heritage studies and monitoring on existing ones.

### 2 Related Work

#### Text classification

Text classification is an essential task in NLP. In the past decades, there have been numerous models proposed from shallow to deep learning models. In shallow learning models, the raw input text is pre-processed to extract the features of the text, such as Bag-of-words (BOW), N-gram, term frequency-inverse document frequency (TF-IDF), word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014). The features are then fed into machine learning classifiers (e.g., Naive Bayes (Maron, 1961) and support vector machine (Cortes and Vapnik, 1995; Joachims, 1998)) for prediction. In deep learning models, deep neural networks are leveraged to extract information from the input data, such as convolutional neural networks (CNN) (Kim, 2014; Johnson and Zhang, 2017), recurrent neural networks (RNN) (Tai et al., 2015; Cho et al., 2014; Howard and Ruder, 2018), attention networks (Yang et al., 2016) and Transformers (Devlin et al., 2019). This work explores the combined application of several popular models including both shallow and deep learning models.

#### Multi-Class and Multi-Label Classification

Compared to binary classification, multi-class classifiers classify the input into one of several categories (Aly, 2005). Multi-label classification is more complex than single-label classification,
which ignore the contextual information in the sentences. More recent works, e.g., ULMFiT (Howard et al., 2018) provide static word embeddings which are pre-trained on massive corpus and fine-tuning on target task. Earlier works (Mikolov et al., 2013; Pennington et al., 2014) provide static word embeddings which ignore the contextual information in the sentences. More recent works, e.g., ULMFiT (Howard and Ruder, 2018) and BERT (Devlin et al., 2019), take the context into account and generate dynamic contextualized word vectors, which have shown excellent performance across many tasks and have been significant milestones in NLP. This task employs the idea of transfer learning and applies both embedding methods.

3 Data and Problem Statement

3.1 Data Collection and Pre-processing

UNESCO World Heritage Centre openly releases a syndication dataset of the properties in XLS format, which includes information of the inscribed World Heritage properties such as ID, name, short description, OUV justification, assigned OUV criteria, et. al.. Among them the field of justification provides a paragraph for each OUV criteria the property fulfills, contributing as the input data for the task. For example, in Venice and Its Lagoon, the paragraph on criterion (iii) shows:

Criterion (iii): With the unusualness of an archaeological site which still breathes life, Venice bears testimony unto itself. This mistress of the seas is a link between the East and the West, between Islam and Christianity and lives on through thousands of monuments and vestiges of a time gone by.

For any inscribed WH property \( p_i \in P \), where \( P \) is the set of all the properties, it may fulfill one or more of the ten OUV criteria. By checking if each criterion is justified for the property \( p_i \), a non-negative vector \( \gamma_i = [\gamma_{i,k}]_{k=1}^{\kappa}, k \in [0, \kappa), \kappa = 10 \) can be formed as the label for the property:

\[
\gamma_{i,k} = \begin{cases} 
1, & \text{if } p_i \text{ meets the } k_{th} \text{ criterion}, \\
0, & \text{otherwise.}
\end{cases}
\] (1)

Meanwhile, the paragraphs \( X_i \) in the justification field of \( p_i \), describing all OUV criteria that \( p_i \) has, are split into sentences. For the \( j_{th} \) sentence \( x_{i,j,k} \) describing the criterion \( k \) possessed by the property \( p_i \), a one-hot vector \( y_{i,j,k} \) can be formed as the ground-truth label for this single sentence:

\[
y_{i,j,k} = e_k \in \{0, 1\}^\kappa.
\] (2)

Each sentence \( x_{i,j,k} \in X_i \) is treated as a sample, with two corresponding labels: the one-hot “ground-truth” label \( y_{i,j,k} \) for the particular sentence, and the multi-class “parental label” \( \gamma_i \) for all sentences belong to the property \( p_i \). Since the sentences were written, revised, and approved by various domain experts at local and global levels during inscription process, the labels can be considered
Table 1: The number of samples that contain each criterion as a label, annotated with C1 to C6 pertaining to cultural heritage and N7 to N10 pertaining to natural heritage. The first three rows show the data split using the field *justification*; the fourth row shows a new dataset only for testing using the field *short description* (SD); the last row shows the potential samples the models can see for each criterion after introducing label smoothing (LS).

| Split       | C1 | C2 | C3 | C4 | C5 | C6 | N7 | N8 | N9 | N10 | Sum         |
|-------------|----|----|----|----|----|----|----|----|----|----|-------------|
| train       | 333| 631| 651| 774| 209| 327| 386| 261| 370| 572| 4514        |
| valid       | 40 | 71 | 83 | 89 | 28 | 49 | 43 | 42 | 42 | 76 | 563         |
| test        | 41 | 79 | 72 | 92 | 35 | 47 | 45 | 32 | 50 | 71 | 564         |
| test in SD  | 815| 1563|1647|2049|554|876|510|344|465|548|9361        |
| seen w LS   | 1077|1747|1832|2131|609|1063|1130|630|1047|1251|12517       |

as having a sufficient “inter-annotator agreement” (Jokilehto, 2008; Nowak and Rüger, 2010).

The following data pre-processing techniques are applied to construct the final dataset used for training: 1) all letters are turned into lower-case; 2) the umlauts and accents are normalized; 3) numbers are replaced with a special <NUM> token; 4) only sentences with a length between 8 and 64 words are kept; 5) the sentences are randomly split into train/validation/test sets with a proportion of 8:1:1; 6) additionally, the official definition sentences of each OUV criterion are appended into the train split with same sentence and parental labels. Furthermore, to give models flexibility to output a class related to none of the existing OUV criteria, an 11th class is introduced by appending an arbitrary weight value $\gamma$ to the end of all $\gamma$ vectors and a 0 to all $y_{i,j,k}$ vectors.

On average, 27.97 ± 11.04 words appear in each sentence. A summary of the number of samples in each split for each OUV criterion is presented in the first three rows of Table 1.

Similarly, the paragraphs $S_i$ in the field *short description* of $p_i$, giving a general introduction of the property, are pre-processed into an additional independent test dataset SD to evaluate the generalizability of the classifiers on unseen data that comes from a slightly different distribution. For those sentences $s_{i,o} \in S_i$, both ground-truth and parental labels are the same as $\gamma_i$ for the property they describe. The total number of samples that contain each criterion in SD dataset is shown in the fourth row of Table 1.

### 3.2 Association between Classes

Jokilehto (2008) summarized the six cultural criteria and the first natural criterion with their main focuses. However, as argued in Section 1, the label classes (OUV criteria) are not mutually exclusive. Still take the criterion (iii) in Venice as an example.

Judging as a domain expert, it is clearly describing criterion (iii) as is labelled, since it explicitly uses the term “testimony” and “archaeological site” from “a time gone by”. However, traces can still be found on other values: 1) as it describes the linkage “between the East and the West”, it also concerns the criterion (ii) of influences among cultures; 2) as it talks about “Islam and Christianity”, a certain degree of religious association also points it to the criterion (vi). In fact, criteria (ii) and (vi) are also justified with Venice. From experience, for properties fulfilling more than one OUV criteria, it is hard to avoid talking about the others while isolating one criterion (Pereira Roders, 2010).

Furthermore, the association between each pair of criteria can be different. The distinction between criteria is generally larger when the pair comes from a different category (cultural v.s. natural). For a pair of criteria from the same category, the association level can also vary. For example, Jokilehto (2008) pointed out that “criterion (i) and (ii) can reinforce each other while (iv) is often used as an alternative”. This complex association pattern can also be seen in the co-occurrence matrix $A_{\kappa \times \kappa} = [a_{k,l}]_{k \times \kappa}$, $k, l \in [0, \kappa)$ of the OUV criteria in all the inscribed properties $P$, where the diagonal entries of the matrix record the number of cases when each criterion is used alone:

$$a_{k,l} = \begin{cases} \sum_i (\gamma_{i,k} \gamma_{i,l}), & \text{if } k \neq l, \\ \sum_i \left[ \frac{\gamma_{i,k}}{\sum_j \gamma_{i,j}} \right], & \text{otherwise.} \end{cases} \quad (3)$$

The intrinsic association implied by this co-occurrence pattern is to be the prior knowledge for the classification task.

### 4 Models and Experiments

#### 4.1 Smoothed True Labels

As is argued in the previous sections, the OUV criteria are not mutually exclusive, and co-justified criteria of a WH property that have a stronger association may be reflected in the sentences describing
a specific criterion. In other word, classifying such sentences is not purely a multi-class classification task. Rather, it also has a multi-label classification characteristic considering the “parental labels” of the properties.

To leverage the problem between the two sorts of tasks, this paper proposes to apply label smoothing (LS) technique with novel variants to combine the “ground-truth” sentence label \( y_{i,j,k} \) and the parental document label \( \gamma_i \) into a single vector \( \tilde{y}_{i,j,k} \) for the training process. Three variants are proposed here: vanilla that reflects the common usage of LS literature by assigning identical “noises” to all classes; uniform that treats all co-occurred criteria in the parental label equally; and prior that weights the co-occurred criteria based on the frequency that the pair co-occurs in matrix \( A_{c \times c} \):

\[
\tilde{y}_{i,j,k} = \begin{cases} f(y_{i,j,k} + \alpha 1), & \text{if vanilla,} \\ f(y_{i,j,k} + \alpha \gamma_i), & \text{if uniform,} \\ f(y_{i,j,k} + \alpha \mu_k \odot \gamma_i), & \text{if prior.} \end{cases}
\]

(4)

Here \( f \) is a translation of the original softmax function so that it maps non-negative real numbers to a distribution that sums up to 1:

\[
f(z)_k = \frac{e^{z_k} - 1}{\sum_{l=1}^{d} e^{z_l} - d},
\]

for \( k \in [0, d) \) and \( z := [z_k]_{d \times 1} \in \mathbb{R}^d_+; \)

\( \alpha \) is a scalar that leverages the effect of LS; \( \mu_k := [\mu_{k,l}]_{(c+1) \times 1} \) is a criterion-specific non-negative vector showing the inter-criteria associations:

\[
\mu_{k,l} = \frac{a_{i,k}}{\sum_i a_{i,k}}, \quad l \in [0, c+1),
\]

and \( \odot \) represents the element-wise Hadamard-Schur product of vectors.

All three variants are considered as options during training, and tuned as hyperparameters together with the scalar \( \alpha \in \{0, 0.01, 0.05, 0.1, 0.2, 0.5, 1\} \). For either variant, the problem is purely multi-class when \( \alpha = 0 \), and becomes multi-label when \( \alpha = 1 \).

The following benefits can be achieved with the use of proposed LS variants: 1) The prior knowledge of the actual association of classes (criteria) are introduced into the training, giving the model chances to learn these intrinsic associations with a soft label; 2) The freedom on the design decision of whether the problem should be multi-class or multi-label is provided for the model training process; 3) The models can potentially see more instances for each class during training with LS, as shown in the last row of Table 1; 4) The computed soft label vector \( \tilde{y}_{i,j,k} \) is mathematically more similar to the prediction vector \( \hat{y}_{i,j,k} \), both of which are discrete “probability” distributions, pushing the use of Cross-entropy Loss closer to its original definition (Rubinstein and Kroese, 2013).

### 4.2 Baselines

Five models are selected as baselines: 1) N-gram (Cavnar et al., 1994) embedding followed by multilayer perceptron (MLP); 2) Bag-of-Embeddings (BoE) using GloVe (Pennington et al., 2014); 3) Gated Recurrent Unit (GRU) (Cho et al., 2014) with Attention (Bahdanau et al., 2014; Yang et al., 2016) using GloVe; 4) Pretrained ULMFiT language model (Howard and Ruder, 2018) further fine-tuned on the full WHL domain dataset; and 5) uncased base BERT model (Devlin et al., 2019). The former three models are trained from scratch, while the latter two are extensively pretrained and fine-tuned on this specific classification task. The model implementation details and the hyperparameter configurations are shown in the Appendix.

### 4.3 Metrics

For the training process, the original Cross-Entropy is used as the loss-function, while three metrics are used to evaluate the model performance as multi-class classification task: 1) **Top-1 Accuracy** which counts the instances when the predicted class with the highest output value matches the ground-truth sentence label; 2) **Top-k Accuracy** which counts the instances when the ground-truth sentence label is among the top k (here k=3) predicted classes with the highest output values; 3) **Macro-averaged F1** which calculates the overall cross-label performance. **Per-class Metrics** (i.e., precision, recall, and F1) for each OUV criteria are also calculated for evaluation purpose.

For the independent SD test set, two metric are defined here to evaluate the model performance as multi-label classification task: 1) **Top-1 Match** which counts the instances when at least one of the parental labels matches the predicted class. 2) **Top-k Match** which counts the instances when at least one parental label is among the top k predicted classes. Arguably, the top-1 and top-k matches are more tolerant extensions of top-1 and top-k accuracy into multi-label classification scenarios.
4.4 Experiment Setup

The experiment consists of three successive steps for each baseline:

1. Grid search within a small range is performed to tune the hyperparameters with a single random seed and the best configuration is selected according to the top-k accuracy on the validation split;

2. LS with different $\alpha$ values under all three conditions (vanilla, uniform, and prior) is tested using the configuration from step 1, repeated with 10 selected random seeds, treated as another group of hyperparameter tuning, saving the best LS configuration according to the performance mean and variance over the seeds;

3. The best LS configuration in step 2 is applied to save a model with the same random seed used in step 1 and evaluated together with the baseline model without LS, both on validation/test splits and on SD test set;

Early-stopping is applied during all training processes based on the top-k accuracy on the validation split. The models are implemented in PyTorch (Rao and McMahan, 2019) and experiments are performed on NVIDIA Tesla P100 GPU (N-gram, GRU+Attn, BERT) and Intel Core i7-8850H CPU (BoE, ULMFiT), respectively. Inference is performed entirely on CPU to test the models’ feasibility in more general contexts when GPU is not available for end-users.

5 Results and Analyses

5.1 Experiment Results

The averaged top-k accuracy of experiments conducted with 10 random seeds are shown in Figure 1. In most cases (except for BoE), the models with LS either strictly or weakly out-perform the baselines (without LS or with vanilla LS). The uniform variant of LS with different $\alpha$ values appears in most baselines. A possible explanation is that uniform LS introduces the prior knowledge from the parental labels as “noise” in a simple way during the training, balancing yet not challenging the “ground-truth” sentence labels (Müller et al., 2019). Yet the complex effect of LS on different baselines invites further investigation.

Table 2 shows the performance of the models with and without LS on the validation split, test split, and SD test set. It can be observed that except for BoE, introducing LS increased the performance of most baselines in most metrics. Generally speaking, the pretrained models dominates the performance, and the highest score for all the metrics occurs in either ULMFiT or BERT, mostly with LS. Still, top-1 accuracy only reaches 71% in the best models, while top-k accuracy manages to reach 94%, suggesting that it would be more reliable to look at the top 3 predictions of the model in this task. The models perform remarkably well in the SD test set, though given a relatively simpler task than in training, roughly proving the generalizability of the classifiers.

Looking at the per-class metrics of the best models in each baseline on the validation and test split, (see Table 3), it is evident that the difficulty for classifying each OUV criterion varies. Table 3
Table 2: The performance of models with and without LS on validation split, test split (top-1 accuracy, top-k accuracy, and averaged macro F1), and independent SD test set (top-1 match and top-k match). The best score for each metric is highlighted in bold, and with underline if the best score occurs in models with LS. The effect of adding LS to each baseline is marked with background colors: blue indicates a rise in performance, red indicates a drop, while grey indicates a tie. The darker background color indicates a larger variation in performance.

Table 3: The average per-class metrics over all models on validation and test splits with LS, and the main focus of each OUV criteria adapted from Jokilehto (2008).

Table 4: The result of independent sample t-test on the per-class metrics between cultural and natural OUV of all models with LS on the test and validation splits.

5.2 Explainability
Although sometimes challenged (Serrano and Smith, 2020), attention mechanisms are believed to be effective for NLP model performance and explainable visualization (Yang et al., 2016; Vaswani et al., 2017; Tang et al., 2019; Sun and Lu, 2020). The same example on OUV criterion (iii) in Venice will be demonstrated here using the best models from the attention-enabled GRU+Attn and BERT.

The poor performance of criterion (v) is consistent with the fact that this class has the smallest sample size (as shown in Table 1); meanwhile criterion (viii) with the second least samples performs reasonably well. This suggests that except for the sample size, the strong associations between the classes also affect the difficulty for NLP models (and probably also for human) to distinguish the nuance of criteria. Criterion (i) has a far poorer precision than recall, suggesting that samples from other criteria, especially from criterion (iv), are easily confused as this one. This is also comprehensible since criterion (i), emphasizing that a property is a masterpiece, can be easily mentioned “by mistake” in the description of criterion (iv) that regards a drop, while grey indicates a tie. The darker background color indicates a larger variation in performance.
to be more confident with the result without losing the association information between the criteria.

GRU+Attn employs a single universal attention mechanism to all inputs, while BERT has 12 attention heads for each of the 12 transformer blocks, both of which manage to capture the meaningful keywords and phrases such as *archaeological, venice, testimony, islam, and monument* in the sentences. Figure 2 visualizes the attention weights in both models with BertViz library (Vig, 2019; Vaswani et al., 2018). As a note, Clark et al. (2019) used probing to find out that some BERT attention heads correspond to linguistic phenomena. In this study, three attention heads from the last layer are found to show relative yet distinct information, which seems to focus on different semantic meanings of the WH OUV criteria. This observation invites further studies.

6 Discussion and Conclusions

This paper presents a new text classification benchmark coming from a real-world problem about UNESCO World Heritage (WH) Outstanding Universal Value (OUV). The problem is essentially a multi-class single label classification task, while the classes are not necessarily mutually exclusive. The prior knowledge of the class association is added to the training process as multi-label features through novel variants of label smoothing (LS), which was originally a regularization technique. The study shows that introducing LS improved the performance on most baselines including the pretrained language models ULMFiT and BERT, reaching a top-3 accuracy of 94.3%. The models also perform reasonably well in an independent test dataset, which suggests that the classifiers have the potential to be further developed and applied in the World Heritage research and practice.

In this study, LS was not tuned together with other hyperparameters, yet still showed an improvement in most baselines. However, the complex effect of LS on different baselines needs more investigation. The top-1 accuracy is limited even on the best models, which is also evident in the literature for non-binary multi-class classification when the labels are not distinct enough (Sun et al., 2019). Applying data augmentation and training supplemental binary classifiers may improve the performance on difficult classes. Moreover, studies on the generalizability and reliability of the models on data from different distributions (e.g. from social media posts, policy documents, or news article) are needed before further application.

The current OUV evaluation and justification process is time-consuming and knowledge-demanding. By innovatively introducing NLP into the field, chances are created to comprehensively investigate the semantic meaning of OUV criteria and the intrinsic associations among them. As argued in Section 5.1, natural OUV criteria may have a clearer definition than cultural ones. This might lead to another round of discussion and even revision of the OUV definitions (Jokilehto, 2008), which is explicitly suggested by World Heritage Committee (WHC) to reflect the evolution of WH concept itself.

This work can aid, but not replace the workload of human stakeholders: for State Parties to identify heritage values through documentation, for ICOMOS and WHC to evaluate and verify the yearly nomination proposals, for researchers to investigate massive official discourse and user-generated content, and for everyone concerned to systematically understand *Their World Heritage* around them. Therefore, this work WHOSe Heritage can be another milestone for the digital transformation of World Heritage studies, aiming at a more socially inclusive future practice.

Figure 2: The attention weights of GRU and BERT models on the exemplary sentences concerning OUV criterion (iii) in Venice. Attention weights of [CLS] token from three attention heads (12-3, 12-6, and 12-12) on the last BERT layer are selected based on observation from BertViz results and plotted together with the attention weights computed from GRU.

7 http://whc.unesco.org/en/criteria/
Broader Impact Statement

This work focuses on exploring and applying NLP techniques to a real-world application of cultural and natural World Heritage (WH) preservation for the sake of social good. The research is to aid the identification and justification of heritage values across the world for various stakeholders including both heritage experts and lay-persons through text classification, as is pointed out in Section 1 and 6. It can lead to better understandings of the OUV criteria and the association among them, yielding chances to eventually amend and clarify some OUV definition which may be ambiguous.

The dataset used in the work is collected by the author(s) from the public website of UNESCO World Heritage Centre via XLS syndication respecting the terms of use and copy rights. The description of the dataset is sufficiently revealed in section 3.1 and the Appendix. All labels used are based on the official OUV justification given by local and global heritage experts and involve no crowd workers or other new annotators. The dataset and the methods used in the paper do not contain demographic/identity characteristics. Once deployed, the model does not learn from user inputs, and it generates no harmful output to users.

BERT and ULMFiT with LS proved to perform best in all investigated metrics. However, there is a trade-off to consider for real-world application. As claimed in the Appendix and Section 5.2, ULMFiT has a relatively short inference time compared to BERT, yet BERT are potentially more explainable due to the attention mechanism. Both models might work optimally for different application scenarios.

Nevertheless, the interpretation of the classification result needs to be carefully conducted by researchers and practitioners, especially during policy decision-making on World Heritage for the social benefit of the entire human species. WH inscription and OUV justification is far more complicated than only reading written texts and identify the described values. Rather, it is a systematic thematic study based on scientific research and always rooted in COMPARATIVE study across the globe (Jokilehto, 2008). This study and the obtained NLP model can be less biased than manual annotation by the experts in the sense that they avoid adding too much implicit “imaginary” information into the written text, but also potentially more biased in the sense that they are highly dependent on the existing OUV description, which may contain historical unfairness and do not necessarily contribute to identify some “universally outstanding value” compared to all other WH candidates.

Researchers and practitioners, especially those outside of Computer Science field, need to be explicitly informed and even warned before usage on the limitations of such models, to avoid automation bias, which shows that people favour the results automatically generated from systems for decision-making (Parasuraman and Manzey, 2010). Failure of the proposed method/system and misinterpretation of the results can lead to severe negative impact. Wrongly under-judging the value of a WH nomination merely based on text classification results and consequently deferring or even refusing the inscription can cause a great loss to human culture in the worst scenario. Therefore, this work only functions as a supplemental tool and/or reference for the understanding/evaluating of World Heritage OUV implied in text descriptions, which will and shall not replace the human effort and/or deviate the expert knowledge in WH decision-making process.

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Supplementary Materials

The data and models presented in this paper can be found in the following GitHub link: https://github.com/zzbn12345/WHOSe_Heritage.

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Appendix

A OUV criteria and Dataset

**OUV Criteria Definitions** As explained in UNESCO (2008), for any property to be inscribed in the World Heritage List, it must satisfy at least one of the ten Outstanding Universal Value (OUV) criteria and meet the conditions of integrity and/or authenticity (Jokilehto, 2008).

However, it is to be stressed that the definition of the criteria is regularly revised by the World Heritage Committee to reflect the evolution of World Heritage (WH) itself. For example, cultural (criteria i-vi, also denoted as C1-C6) and natural (criteria vii-x, also denoted as N7-N10) OUV used to be justified apart as two sets. Since 2004, the two sets are combined. Though WH properties are usually justified with OUV from one category (cultural or natural), within the domain of mix heritage and cultural landscape, OUV from both categories can co-occur in one property (e.g., Mount Tai has all first seven OUV).

**Association between Criteria** Among all the 1121 properties inscribed in the World Heritage List up to 2019, only 188 are justified with only one criterion. The distribution of the total number of OUV criteria \( \sum_{k=0}^{\kappa} \gamma_{i,k} \) a property is justified with.

| \( \kappa \) | Count | Proportion | Example |
|---|---|---|---|
| 1 | 188 | 16.75% | Sydney Opera House |
| 2 | 468 | 41.71% | Babylon |
| 3 | 304 | 27.09% | City of Bath |
| 4 | 103 | 9.18% | Yellowstone National Park |
| 5 | 34 | 3.0% | Acropolis, Athens |
| 6 | 4 | 0.36% | Venice and its Lagoon |
| 7 | 2 | 0.18% | Mount Taishan |

Table 5: The distribution of the total number of OUV criteria \( \sum_{k=0}^{\kappa} \gamma_{i,k} \) a property is justified with.

Regardless of the number of co-justified criteria for each property, the co-occurrence matrix \( A_{\kappa \times \kappa} \) of all OUV criteria is shown in Figure 3. The nor-
data $x_{i,j,k}$ leads to a flowering in the creation of calvaries in europe
Criterion (iv) $[0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]$
parental label $\gamma_i$ $[0, 1, 0, 1, 0, 0, 0, 0, 0, 0, .2]$
sentence label $y_{i,j,k}$ 18 (tokens)
property ID $\mu_k$ 905
data split train

Table 6: An example of data sample.

Dataset Distribution An example of data sample is shown in Table 6, with the attributes of text data $x_{i,j,k}$, sentence label as discrete index $k$, sentence label as one-hot vector $y_{i,j,k}$, parental label as vector $\gamma_i$, sample length $|x_{i,j,k}|$, index of parental WH property $i$, and the data split. The distribution of sample length in terms of number of words in the sentence is shown in Figure 4. The three data splits and the independent test dataset SD roughly have the same distribution in terms of sentence length.

B Model Implementation Detail

For all baselines, Adam (Kingma and Ba, 2017) is used as the optimizer with L2 regularization. Hyperparameter tuning is conducted as grid-search within a small range for each one being searched (and/or selected according to common experience if not mentioned), based on the top-k accuracy on validation split with an early-stopping criteria of 5 epochs, if not explicitly mentioned below. The models are implemented in PyTorch (Rao and McMahan, 2019) and experiments are performed on NVIDIA Tesla P100 GPU (N-gram, GRU+Attn, BERT) and Intel Core i7-8850H CPU (BoE, ULMFiT), respectively.

N-gram The N-gram model used the TfidfVectorizer from Scikit-learn Python library (Pedregosa et al., 2011) to get an embedding vector of all 1-grams and 2-grams in the sample that appeared at least twice in the vocabulary. The embedding vectors are then fed in a 2-layer Multi-layer Perceptron (MLP) to get the model prediction. Hyperparameter tuning is performed on the size of the MLP hidden layer in \{50, 100, 150, 200\}, batch size in \{64, 128, 256\}, L2 in \{0, 1e-5, 1e-4\}, and dropout rate in \{0.1, 0.2, 0.5\} with 108 configurations. The best configuration of the model applied in later experiments of Label Smoothing (LS) has a hidden dimension of 200, batch size of 128, L2 of 1e-5, learning rate of 2e-4, and dropout rate of 0.5.

BoE The Bag-of-Embedding (BoE) model used the 300 dimension GloVe embeddings, which is set to be tunable during training. Only words that have a higher frequency than a threshold in the full dataset will be kept, while the others will be transformed to a special <UNK> token. The word embeddings of all words in the sentence is averaged before fed to a 2-layer MLP. Hyperparameter tuning is performed on the size of the MLP hidden layer in \{50, 100, 150, 200\},
batch size in \{64, 128, 256\}, and frequency threshold in \{1, 3, 5\} with 36 configurations. The best model has a hidden dimension of 200, batch size of 64, cut-off frequency of 1, L2 of 1e-5, learning rate of 5e-4, and dropout rate of 0.1.

**GRU+Attn** The GRU+Attn model used the 300 dimensional GloVe embeddings, which is frozen during the training. The embedding sequence is then fed into a GRU network. Word-level attention (Yang et al., 2016) is applied to compute the sentence vector by a learned word context vector and the last hidden state of the GRU. The sentence vector is fed to a 1-layer feed-forward network for the output of the model.

Hyperparameter tuning is performed on the size of the hidden layer in GRU in \{64, 128, 256\}, whether or not to use bi-directional GRU, batch size in \{64, 128, 256\}, L2 in \{0, 1e-5, 1e-4\}, learning rate in \{1e-3, 5e-4, 2e-4\}, and dropout rate in \{0, 0.1, 0.2, 0.5\} with 648 configurations. The best model is a uni-dimensional GRU with hidden dimension of 128, batch size of 256, L2 of 1e-5, learning rate of 1e-3, and dropout rate of 0.1.

**ULMFiT** The ULMFiT model employs the idea of Universal Language Model Fine-tuning from a general-domain pretrained language model on Wikitext-103 with AWD-LSTM architecture (Howard and Ruder, 2018). A domain-specific language model is then fine-tuned with the full UNESCO WHL dataset including SD using fastai API (Howard and Gugger, 2020). One epoch is trained with a learning rate of 1e-2 with only the last layer unfrozen, reaching a perplexity of 46.71. Then the entire model is unfrozen and further trained for 10 epochs with a learning rate of 1e-3, obtaining a fine-tuned WH domain-specific language model reaching a 30.78 perplexity.

The encoder of the fine-tuned language model is loaded in PyTorch followed by a Pooling Linear Classifier\(^9\) for classifier fine-tuning. Gradual unfreezing is applied in a simplified manner to prevent catastrophic forgetting: 1) for the 1st epoch, only the decoder is unfrozen and trained with a learning rate of 2e-2; 2) for the 2nd to 4th epoch, one more layer is unfrozen each time and trained with a learning rate of 1e-2, 1e-3, and 1e-4, respectively; 3) from the 5th epoch onward, the full model is unfrozen and trained with a learning rate of 2e-5. An early-stopping criteria of 3 is applied.

Table 7: The multiple comparison of means using Tukey HSD on the F1 metric of OUV classes by all models on both validation and test splits within both cultural and natural categories.

| Class 1 | Class 2 | Mean Diff | p value |
|---------|---------|-----------|---------|
| Cultural OUV | | | |
| C1 | C2 | -11.38*** | .006 |
| C1 | C4 | 11.17*** | .007 |
| C2 | C4 | 10.32** | .015 |
| C2 | C5 | 22.55*** | .001 |
| C3 | C5 | 16.00*** | .001 |
| C4 | C5 | 12.23*** | .002 |
| C5 | C6 | -16.26*** | .001 |
| Natural OUV | | | |
| N7 | N9 | 10.90*** | .001 |
| N7 | N10 | -8.12** | .003 |
| N8 | N9 | 8.94** | .001 |
| N8 | N10 | -10.08*** | .001 |
| N9 | N10 | -19.03*** | .001 |

\(^9\)https://fastai1.fast.ai/text.models.html

No extensive hyperparameter tuning is performed since: 1) tuning ULMFiT is expensive on CPU; 2) the hyperparameter configuration from experience suggested by Howard and Gugger (2020); Howard and Ruder (2018) already performs reasonably well; 3) the purpose of this study is not necessarily finding the best hyperparameter. The final model uses batch size of 64, L2 of 1e-5, and the default dropout rate for the decoder.

**BERT** The BERT model uses the uncased base model using The Transformers library (Wolf et al., 2020). The pooler output processed from the last hidden-state of the [CLS] token during pre-training is fed into a 1-layer feed-forward network to fine-tune the classifier (Sun et al., 2019). An early-stopping criteria of 10 is applied.

Hyperparameter tuning is performed on the batch size in \{16, 24, 48, 64\}, L2 in \{0, 1e-5, 1e-4\}, and dropout rate in \{0, 0.1, 0.2\} with 36 configurations. The best model uses batch size of 64, L2 of 1e-4, learning rate of 2e-5, and dropout rate of 0.2.

**LS Configuration Tuning** A single random seed 1337 is used for hyperparameter tuning. Afterwards, ten random seeds in \{0, 1, 2, 42, 100, 233, 1024, 1337, 2333, 4399\} are used to tune the LS configuration (3 variants all with 7 α options). The best LS configuration is selected based on the sum of the lower bound of 95% confidence interval on both top-1 and top-k accuracy. The best LS configuration is then used to evaluate the model per-
The model performance in terms of resource occupancy and inference time. Inference is conducted on Intel Core i7-8850H CPU. Inference time per Item shows the average time the model uses to make prediction on one sentence. And Inference time for SD shows the total time the model needs to fully process and predict the independent Short Description (SD) test set.

### C Extended Model Performance

The statistic analyses including independent $t$-test, one-way ANOVA, and post hoc comparisons are conducted with Scipy\(^\text{10}\) and Statsmodels\(^\text{11}\) libraries. Table 7 shows the result of post hoc comparisons using the Tukey HSD test for the one-way ANOVA conducted on the F1 metric of cultural and natural OUV classes by all models. Only intra-category pairs of OUV criteria that are significantly different with each other are shown.

Table 8 shows some further information on the model performance in terms of training resource utilization, model size, and inference time. Training are conducted on CPU or GPU, respectively, while inference is fully conducted with CPU.

It can be noted that the best-performing models ULMFiT and BERT also consume the most resources, in terms of training time and infrastructure usage, and have the largest model sizes. Though most time-consuming during training, ULMFiT takes a remarkably short time for inference on CPU compared to BERT. This suggests that ULMFiT might be an optimal choice for further development and application.

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\(^{10}\)https://docs.scipy.org/doc/scipy/reference/stats.html

\(^{11}\)https://github.com/statsmodels/statsmodels