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Personalized Document Template Recommendations Using Machine Learning

ABSTRACT

When creating a new document, a user typically starts from a blank document in the default template and must manually apply the desired formatting for the type of document. The types of documents and the frequency with which each type of document is created varies across users. However, word processors do not currently include a mechanism to select a document template based on the formatting of the frequent document types created by a user.

This disclosure describes techniques to present personalized recommendations for suitable templates based on the documents and templates a user constructs frequently, thus saving the user the time and effort of manual formatting. With user permission, key parameters for each document previously created by the user are used to train a machine learning model in which K-means clustering is employed to output a ranked set of recommended document templates. The recommended document templates can be presented when the user creates a new document as a dialog or a sidebar.

KEYWORDS

- Document template
- Document formatting
- Word processor
- Document editor
- K-means clustering
- Probabilistic encoding
- Personalized template

BACKGROUND

Word processing applications are used to create a wide variety of documents, ranging from simple notes to technical documentation that has specific formatting requirements. When creating a new document, a user typically starts from a blank document in the default template and must manually apply the desired formatting for the type of document. Alternatively, the user can create and save a template for each document type and apply it manually when constructing the document.

The types of documents and the frequency with which each type of document is created varies across users. For instance, one user may mostly create official letters while another may predominantly write engineering notes with a stylish header. For a given user, certain types of documents with specific formatting styles are likely to be created more often than any other type. For instance, the majority of documents created by a particular user might be of one of three types: a personal note, a presentation-like outline, and a white paper with institutional headers and footers. However, word processors do not currently include a mechanism to select a document template based on the formatting of the frequent document types created by a user.

DESCRIPTION

This disclosure describes techniques to provide recommendations for suitable document templates personalized to a user. With specific user permission, the recommendations can be derived by surfacing the template types most likely to be suitable for the user based on analyzing documents and templates the user has previously saved. The recommended document templates can be presented when the user creates a new document with a suitable user interface (UI) mechanism, such as a dialog or a sidebar. If none of the recommended templates are suitable, the user can simply begin with a blank document in a default template as usual, or manually pick a template from a template library.

To identify the recommended templates for a given user, key parameters of documents saved by the user can be obtained. Examples of key parameters include:

- Existence of a header;
- Type and size of the header font;
- Type and size of the font in the document body;
- Scale of the page;
- Presence of watermarks;
- Options for custom formatting (e.g., two-column mode);
- Page orientation (i.e., landscape or portrait);
- Existence of footnotes; etc.

Each key parameter can be represented by a variable of suitable type (e.g., Boolean, float, etc.). With user permission, the set of key parameters for documents previously created or edited by the user can be used as a training set for a machine learning model to train it to output a ranked set of recommended document templates based on the input parameters. If the user permits, the training set can be expanded with newly saved documents.

Of the clusters that the user is deemed to favor, the top K can be used to recommend the corresponding document template options to the user. The number of top clusters K can be chosen a priori based on the desired number of template recommendations. While an overly small K can result in combining formatting options across multiple document types, an overly large K can lead to recommending too many templates that match one-off document formats not meant for reuse. The hyperparameter K can be fine-tuned based on appropriate user input. For example, users can indicate the number of template recommendations they would like to receive via surveys or UI options.

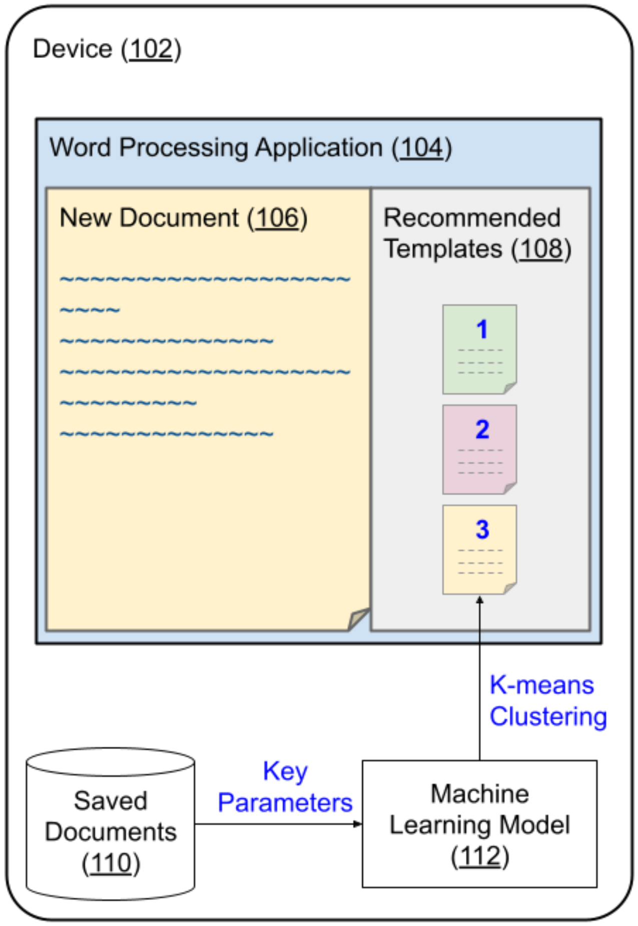

Fig. 1: Recommending templates for a new document based on previous documents

Fig. 1 shows an operational implementation of the techniques described in this disclosure. A user initiates a new blank document (106) within a word processing application (104) which may be an application executing on user device (102) or provided via a web browser executing on the user device. Three template recommendations (108) for formatting the document are shown as a sidebar within the application. As mentioned above, the personalized recommendations are derived with user permission by extracting key parameters from the user’s previously created documents (110) and analyzing them with a trained machine learning model (112). The model operation is based on K-means clustering as described in more detail below.

The list of M such variables corresponding to key document parameters can be treated as a mixed-variable embedding vector in M-dimensional hyperspace. In such a vector, discrete variables (e.g., Boolean, integer, etc.) can be interpreted as continuous, e.g., values of {0, 1}in Boolean form can be approximated to be [0, 1] in the real interval. Such formulation permits the application of vanilla mixed-variable K-means clustering on the training set of N documents saved by the user to cluster the variables into those which the user favors and those which are rarely used.

The output of the K-means clustering algorithm yields K clusters wherein each embedding list is assigned to one of K clusters. For instance, Cluster 1 can contain 13 data points from the embedding list, Cluster 2 can be composed of 3 data points from the embedding list, and so on until Cluster K which can contain 5 data points from the embedding list. The clusters can then be sorted from highest to lowest based on the number of data points from the embedding list contained within a cluster. A suitable filtering scheme can be employed to analyze the sorted clusters and remove any that contain embeddings that would result in a template that the user is unlikely to reuse. For instance, clusters that indicate a sharp drop-off in the number of data points (e.g., from 9 data points to 3) or low number of data points in absolute terms (e.g., 1 or 2) can be filtered out.

The mixed-variable list of embedding data points for each cluster that remains after filtering can be summarized as a corresponding template recommendation via a suitable nonlinear operation on each variable. For instance, all float variables can be pooled as a simple mean, Boolean variables can be determined based on consensus voting, etc. For example, a cluster that contains three embeddings, [Boolean 1, float 0.2, float 0.7], [Boolean 1, float 0.4, float 0.6], and [Boolean 0, float 0.6, float 0.5], can be summarized with the embedding [Boolean 1, float 0.3, float 0.6].

With user permission, the techniques can be implemented within any document preparation application running locally on a user device or provided via a browser. The machine learning model can be deployed locally on the user device or on the cloud. Documents previously saved by the user can be obtained from those saved locally on the device on which the user is creating a new document. Alternatively, or in addition, documents previously created by the user can be obtained from the user's other devices and/or from the cloud. Automatically generated template recommendations that can be readily selected and applied to a document can save the time and effort of manually creating and selecting templates for frequently constructed document types, thus making the user experience (UX) of creating new documents more efficient. Recommendations are generated based on document formatting of prior documents. The user can restrict or deny permission to certain documents and/or portions of documents that are accessed for such purposes. Once the training is completed, no user document data is stored or utilized.

Further to the descriptions above, a user may be provided with controls allowing the user to make an election as to both if and when systems, programs or features described herein may enable collection of user information (e.g., information about a user's documents, word processing application, or a user's preferences), and if the user is sent content or communications from a server. In addition, certain data may be treated in one or more ways before it is stored or used, so that personally identifiable information is removed. For example, a user's identity may be treated so that no personally identifiable information can be determined for the user. Thus, the user may have control over what information is collected about the user, how that information is used, and what information is provided to the user.

CONCLUSION

This disclosure describes techniques to present personalized recommendations for suitable templates based on the documents and templates a user constructs frequently, thus saving the user the time and effort of manual formatting. With user permission, key parameters for each document previously created by the user are used to train a machine learning model in which K-means clustering is employed to output a ranked set of recommended document templates. The recommended document templates can be presented when the user creates a new document as a dialog or a sidebar.