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Ryerson University



BSc. Eng. in Computer Sc. & Eng. **MSc in Computer Science** MSc in Data Science and Analytics

Workplace Communication Program Teach in Higher Education

Linkedin Learning IBM Data Science/CognitiveAl SkillSoft

8112223 Canada Inc. JustEtc Social Services







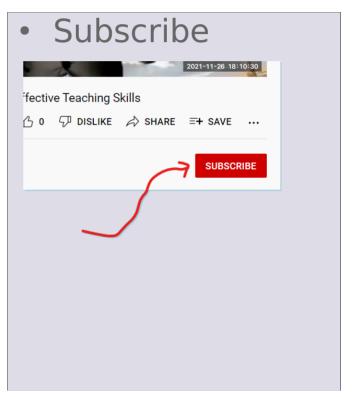
Ilenkaa*



Bal Yout

Youtube Listen Faster/Slower

Watch at 2x speed or 1.5x speed ດດ Annotations Auto 720p > Ruk is 0 + Vers is 25 • Med non 😯 40 🚹 ersi s z 86 🥌 edihah



Misc

- Buy the courses
 - https://ShopForSoul.com
 - http://sitestree.com/training/
 - http://bangla.salearningschool.com/
- Get access to our LMS

- Advantages
 - Discussion
 - Chat
 - Live Sessions
 - Select topics to create videos on
 - Q & A
 - Free Courses

- Regular expression to extract data and information from text
- Tokenization using NLTK or similar
 - Word token
 - Sentence tokenization
 - Utilize regular expression
- Lemmatization using NLTK
- Stemming using NLTK or similar
- Remove stopwords from text
 - Then tokenize
 - Do lemmatization and stemming after stop word removal

- NLP: Write code to remove punctuations from text.
- NLTK: Take stop words list from library. Add your own stop words to the list
 - Then remove stop words from a text
- Write N-Gram (Bi Gram, Trigram) code using frequence as the measure
- Write N-Gram (Bi Gram, Trigram) code using collocated words as the measure
 - What are collation words
 - Find a library method or a 3rd party implementation, use it as well
 - Compare your output with the library/3rd party one
 - Print top few N-grams

- Find about NLTK methods/features such as
 - ngram_fd
 - ngram_fd.items()
 - dir(trigrams)
 - help(trigrams.ngram_fd)
 - nbest
 - TrigramAssocMeasures
 - raw_freq
 - help(TrigramAssocMeasures)

- NLTK features for
 - MLE (Maximum Likelihood Estimate) and Laplace smoothing
- Implement
 - trigrams based smoothing using Laplace and Kneser Ney algorthms
- Implement
 - Laplace smoothing
 - Bigram, trigram
 - Measure the preplexity
 - Measure prepexity as
 - a) Logbase2Prob= Sum-for-alltrigrams(log2(P(w3|w1,w2)) (b)Ent=(-1/tokens-intest)x Logbase2Prob (c) Power(2, (ent))

- Write a program to predict the next few words
 - Based on bi-gram and tri-gram
 - Based on a sample text
 - Use train and test approach
- Study this implementation
 - https://github.com/smilli/kneser-ney
 - Utilize utenberg corpus is required

- Using Penn Treebank, do POS tagging to a text
 - http://www.ling.upenn.edu/courses/Fall_2003/ling001/ penn_treebank_pos.html
- Find out what are these
 - Treebank corpus and Brown corpus
 - Can you use these for the POS tagging task above
- Write short essay on
 - Chunk grammar
 - http://www.nltk.org/book/ch07.html.

- From some example text
 - extract three different chunks of your choice: e.g., coocurrences of adjectives and nouns, co-occurences of determiner, adjectives and nouns, extractions of all types of nouns, etc.
 - Learn on how to train a custom tagger at
 - http://www.nltk.org/book/ch05.htm
- Train an HMM model on the sentences of Brown corpus. Find out the accuracy of your trained HMM model on the sentences in test data

- Use NLTK's tagger to predict the tags and determine accuracy of prediction.
- Read on
 - Maximum Entropy Classifier (MaxEnt)
 - Why MaxEnt is highly accurate
- Read on a decision tree classifier for POS tagging.
 - http://nlpforhackers.io/training-pos-tagger/

- Classify text using
 - Naive Bayes
- Use movie data from here and classify the reviwes to be positive or negative. Use train and test
 - http://ai.stanford.edu/~amaas/data/sentiment/
 - load_files scikit-learn
 - CountVectorizer
- Modify the above implementation
 - Get rid of the words occurring in more than 1000 documents
- Redo the above implementation after modifying the text
 - Such as add Not when you see a negative word, and till the first punctuation

- Use the sentiment lexicon below
 - http://sentiment.christopherpotts.net/lexicons.html
 - Create two features
 - Positive words count
 - Negative words count
- Filter out some words using POS tagging
 - Keep adjectives, verbs, and nouns
 - And then try the sentiment analysis
 - i.e. text classification

- Try this example on Neural Network and text classification
 - https://machinelearningmastery.com/tutorial-first-neural-network-python-keras/ (another beginner tutorial)
 - Try to improve the accuracy
- Train a Neural network with embedding
 - Use the IMDB database as above
 - For text classification
 - Measure the performance and compare the result with Naive Bayes

- Repeat the text classification after replacing negative words wit
 - NOT
- Glove: https://nlp.stanford.edu/projects/glove/
- Pretrained word to dense vectors
- Use glove for a multi-label classification problem
- Use glove and build a binary classifier
 - Pick one of the toxicity columns as the class
 - Classification for Wikipedia comments

- "Make a binary classifier for each class, and assign multiple labels (classes) to each test record. Evalute your accuracy for multiple classes. This is little more work but is more rewarding as a learning experience."
 - Use Glove
 - And wikipedia comments

- Try the name entiry recognition information and example
 - https://www.depends-on-the-definition.com/sequence-tagging-lstm-crf/
 - https://www.kaggle.com/abhinavwalia95/entity-annotated-corpus/version/4#ner_dataset.csv
- Create a Bi-directional LSTM (RNN)
 - For Name Entity Recognition
- Modify the NER example using
 - Glove
- Concatenate each word with POS tagging
 - And then adjust the LSTM/RNN for NER

- Implement Knee/Elbow method of text clustering
- Determine purity of clusters
- Utilize Bernoulli mixture model of clustering
- Explain the Bernoulli mixture model of clustering model as can be seen in
 - https://github.com/manfredzab/bernoulli-mixture-models
 - https://github.com/schwannden/MNIST_mixture-ofbernoulli

- Gaussian Mixture models of clustering
 - http://scikit-learn.org/stable/modules/mixture.html#mixture
- Implement LDA topic modeling algorithm
 - Utilize train/test
- Implement PLSA topic modeling algorithm
- Utilize PLSA topic modeling algorithm from Scikitlearn and apply on a dataset

- Read the Topic Modeling blog at
 - https://nlpforhackers.io/topic-modeling/
- Implement
 - CountVectorizer (Freq)
- Take a set of text/articles/news
 - Train LDA on the data and find the top topics
 - Apply EM if applicable
- Implement PLSA topic modeling algorithm
 - TruncatedSVD
- Modify the code in the URL to get rid of noise from the tokens. Remove
 *,/,-,=,,_ or similar

- Implement LDA and PLSA
 - And apply on some Gutenberg project data
 - Find the topics
- Use LDA, PLSA to find topics
 - Use these topics as features for Naive Bayes
 - Then implement a Naive Bayes classifier
 - Find: accuracy, precision and recall

- Read on Gensim
 - https://radimrehurek.com/gensim/models/ldamodel.html
 - Implement LDA
 - Use alpha and beta
 - Use Gensim

- Implement Textrank algorithm
 - Use Gensim
- Take articles from the Internet
 - Implement text summarization
 - Implement keyword extraction using Gensim
- Implement Naive Bayes classifier as below
 - Find 100 key phrases/keywords from each document/review
 - Merge these keywords and
 - Filter these keywords from the documents
 - Then with the remaining data train and implement Naive Bayes
 - Calculate accuracy, precision, and recall
- Implement ROUGE metric for text summarization
 - "ROUGE, or Recall-Oriented Understudy for Gisting Evaluation, is a set of metrics and a software package used for evaluating automatic summarization and machine translation software in natural language processing" Wikipedia