FUNCTIONAL PROGRAMMING
CS-IS-2010-1
FINAL PROJECT PRESENTATION

Haskell Scraper & Code-Text Separator

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Codebase link: https://github.com/SaptarishiD/haskell-scraper

Introduction

- Separate text and code from text source
- Useful for software development information & knowledge extraction
- Implement Naïve Bayes classifier from scratch
- Learnt Haskell starting from no experience
- Got idea of software specifications and development

Motivation

Types at compile time, no types at run-time

The title of this section is a "one short sentence" explanation of what type erasure means. With few exceptions, it only applies to languages with some degree of compile time (a.k.a. *static*) type checking. The basic principle should be immediately familiar to folks who have some idea of what machine code generated from low-level languages like C looks like. While C has static typing, this only matters in the compiler - the generated code is completely oblivious to types.

For example, consider the following C snippet:

```
typedef struct Frob_t {
  int x;
  int y;
  int arr[10];
} Frob;

int extract(Frob* frob) {
  return frob->y * frob->arr[7];
}
```

When compiling the function `extract`, the compiler will perform type checking. It won't let us access fields that were not declared in the struct, for example. Neither will it let us pass a pointer to a different struct (or to a `float`) into `extract`. But once it's done helping us, the compiler generates code which is completely type-free:

```
0:   8b 47 04                mov    0x4(%rdi),%eax
3:   0f af 47 24             imul   0x24(%rdi),%eax
7:   c3                      retq
```

The compiler is familiar with the stack frame layout and other specifics of the ABI, and generates code that assumes a correct type of structure was passed in. If the actual type is not what this function expects, there will be trouble (either accessing unmapped memory, or accessing wrong data).

A slightly adjusted example will clarify this:

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For example, consider the following C snippet:

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```

Some other use cases

- Developer Emails at company
- StackOverflow Q & A
- Training Language Models
- Any area where language and code are together

Literature Survey

- **Papers**
  - Regex and programming language specific
  - Naive Bayes with bigrams & island parsers (specific to Java)
  - Variety of heuristics & island parsing
  - Hidden Markov Models

Literature Survey

- **Pre-existing libraries**

  - HMM library : **`hmm`**
  - **`NaiveBayes`**

- Decided to implement lightweight algorithm from scratch instead of heavyweight ML methods

Problem Statement & Requirements

Assigned Problem Statement

Develop a scraper using Haskell to extract text and code snippets separately.

1. **Input**: Scrape the text and code snippets from the given text source

2. **Output**: A Word document containing the text and `.txt` file containing the code.

3. **Method**: Write the algorithm to scrape (you can use the `tagsoup` library) and all the input-output facilities using Haskell. Do not use any other language.

Requirements

- The user shall be able to give any text source as input.
- The scraper shall get all the code snippets of the source and write it into a Plaintext file.
- The scraper shall get all non-code text of the source and write it into a Word Document.

Specifications

- The user will be able to enter a text source as input, whose code and non-code parts they wish to be separated.
- The scraper will parse the contents of the text and separate the code snippets from the rest of the text.
- The scraper will output a `.docx` file containing the textual content.
- The scraper will output a `.txt` file containing the code snippets.

Analysis

- Various ways to solve the problem
- Boils down to classification of every line as text or code
- Reasonably restrict ourselves to text sources with newlines
- Don’t consider completely unstructured data
- Don’t go more granular than a line
- Consider text as natural language

Scope & Methodology

Scope

- Fairly broad range of inputs that are structured with newlines
- Classify each line as code or text without classifying *within* each line
- Consider text as natural English language, not as some other non-code or non-English textual content

Methodology

- **Overview**
  - Build and train Naïve Bayes classifier on custom data
  - Use calculated probabilities to classify each line in the text source
  - Combine all code and natural language separately

Methodology

- **Naïve Bayes Classification**

Goal**:** For each line, find the best class

$$\hat{c} = \mathrm{argmax}_c\, \mathbb{P}(c|l) = \mathrm{argmax}_c\, \mathbb{P}(c|t_1, t_2, \ldots t_k)$$

Vocabulary: All words in training data

Classes: Code and Text

Instead of just the terms, consider all words with indicator

- For each line i in text source, have binary feature vector for presence of vocabulary word j

$$l_{ij} \begin{cases} 1, & \text{if } w_j \in l_{ij} \\ 0, & \text{otherwise} \end{cases}$$

- Bag of Words approach
- Make Naïve Bayes assumption of independence of words

$$\mathbb{P}(l_{i1} \ldots l_{in} | y) = \prod_{j=1}^{n} \mathbb{P}(l_{ij} | y).$$

$$\hat{c} = = \text{argmax}_c \left(\mathbb{P}(l|c) \times \mathbb{P}(c)\right) = \text{argmax}_c \left(\mathbb{P}(c) \times \prod_{j=1}^{n} \mathbb{P}(l_j|c)\right)$$

- Work in logspace due to numerical precision and underflow

$$\text{argmax}_c \left(\log \mathbb{P}(c) + \sum_{j=1}^{n} \mathbb{P}(l_j|c)\right)$$

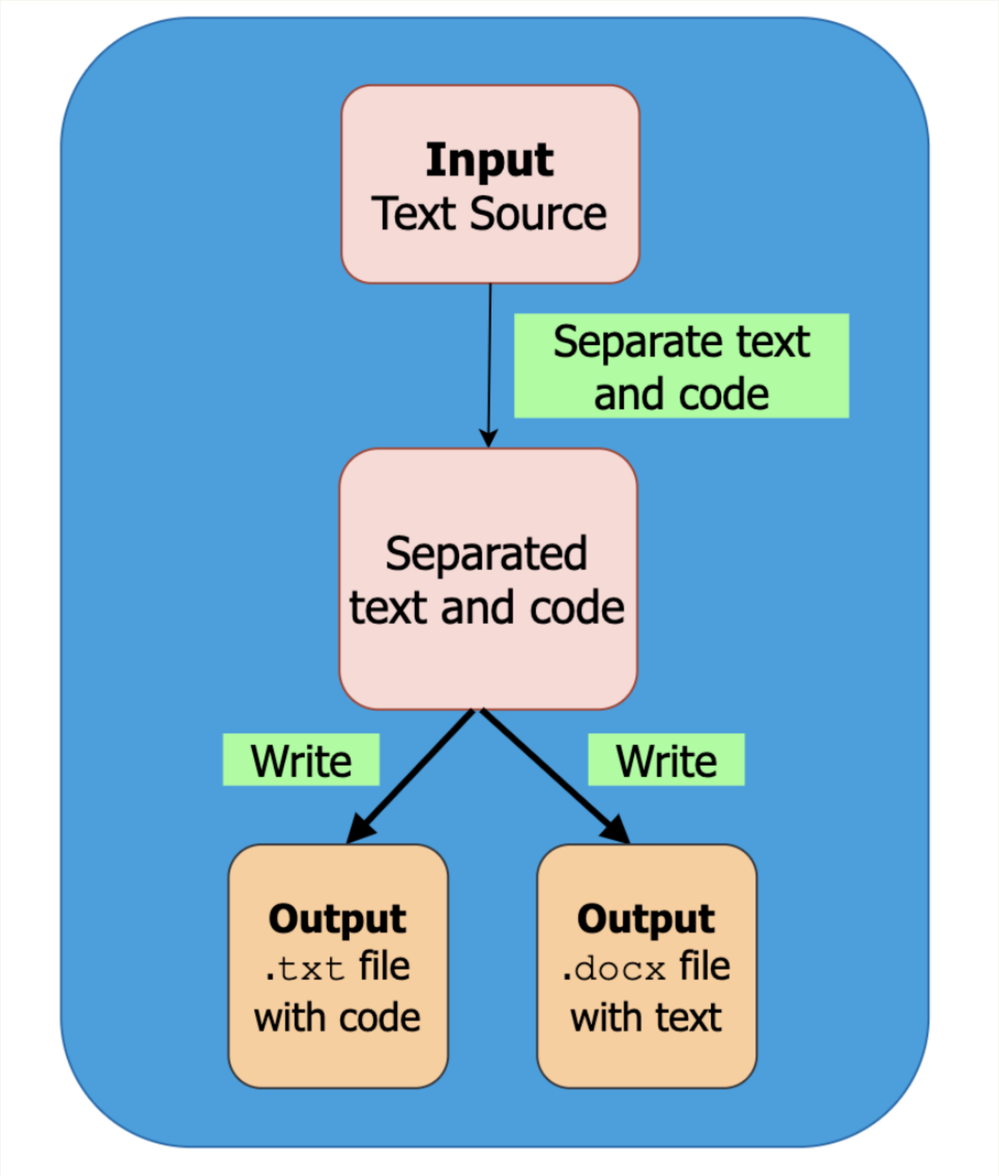
- Calculate probabilities
- Avoid 0 probabilities with Laplace Smoothing
- Count occurrences of *j-th* word in line l in class c and count all words in class c

$$\mathbb{P}(l_j|c) = \frac{count(l_j, c) + \alpha}{\beta + \sum_{j=1}^{n} count(l_j, c)}$$

- Prior probability of each class is simply it's percentage of the training data

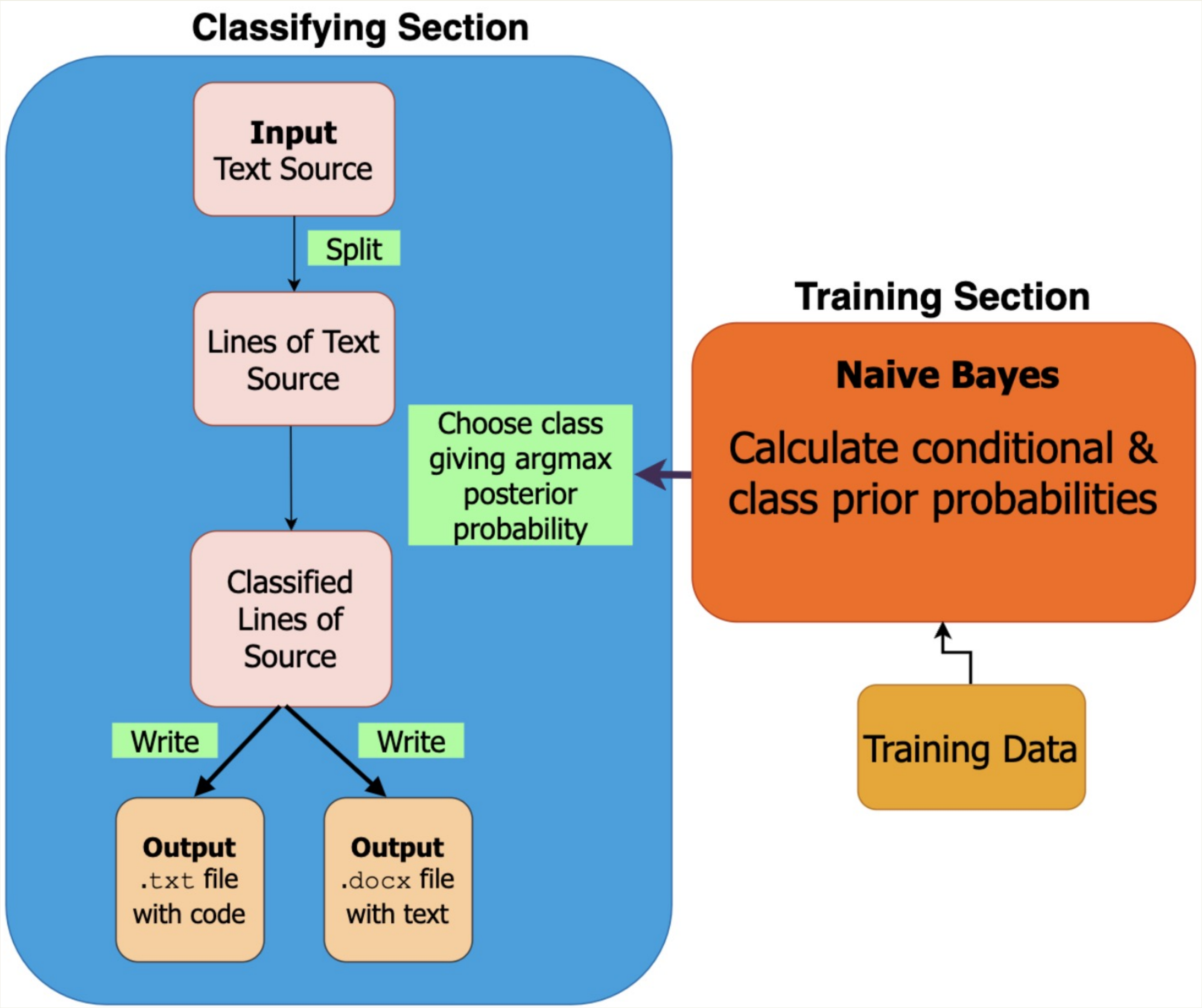
Architecture

Code-Text Separation Pipeline



Design

Classifying Pipeline and Training Section



Work Done

Implementation Details

File Structure

```
scraper
|-- app
|    | -- Main.hs (main driver code)
|-- test
|    |-- Spec.hs (tests)
|-- src
|    |-- Lib.hs (implementation of functions)
|-- input
|    | -- lang_train.txt (training data)
|    | -- code_train.txt (training data)
|-- cases
|    | -- code_test{1-7}.txt
|    | -- lang_test{1-7}.txt
|-- output_files
|    | -- NB_code_class.txt (code snippets)
|    | -- NB_lang_class.docx (textual content)
```

Main.hs

Classification and training pipeline

```
read_text_source <- readFile "input/sample.txt"
let text_source = lines read_text_source -- newlines
let lang_train = "input/lang_train.txt"
let code_train = "input/code_train.txt"
mydata <- Lib.readTraining lang_train code_train
let lang_data = fst mydata
let code_data = snd mydata
let trainedModel = Lib.trainNaiveBayes lang_data code_data

let final_classes = Lib.classifyNaiveBayes text_source trainedModel
let mapping = zip text_source final_classes
let code_class = [x | x <- mapping, snd x == 0]
let lang_class = [x | x <- mapping, snd x == 1]
writeFile "output_files/NB_code_class.txt" (unlines (map fst
↪   code_class))
writeToDocx "output_files/NB_lang_class.docx" (unlines (map fst
↪   lang_class))
```

Lib.hs : trainNaiveBayes

```haskell
-- NLA refers to the hmatrix library
trainNaiveBayes :: [String] -> [String] -> (( Double, ([Double] ,
↪  [Double]) ), Vocabulary )
-- the strange output type is due to packaging various things together
trainNaiveBayes natural_data source_data =
    let source_words = concat (getWords source_data) -- [String]
        natural_words = concat (getWords natural_data)
        unique_src_words = getUniqueWords source_words
        unique_natural_words = getUniqueWords natural_words
        vocab = unique_src_words ++ unique_natural_words
        xTrain_src = myVectorizer vocab (source_data)
        xTrain_lang = myVectorizer vocab (natural_data)
        sourceCodeMatrix = xTrain_src
        naturalLanguageMatrix = xTrain_lang
        -- NLA.Matrix Double -> [Int]
        sum_src_cols = sumCols sourceCodeMatrix
        sum_lang_cols = sumCols naturalLanguageMatrix
        src_len = length source_data
        natural_len = length natural_data
        xgivenY_src = calcXGivenY src_len sum_src_cols
        xgivenY_lang = calcXGivenY natural_len sum_lang_cols
        prob_src_prior = (int2Double src_len) / (int2Double src_len +
        ↪  fromIntegral natural_len)
    in ((prob_src_prior, (xgivenY_src,xgivenY_lang)), vocab )
```

Lib.hs :
classifyNaiveBayes

```haskell
classifyNaiveBayes :: [String] -> (( Double, ([Double] , [Double]) ),
↪  Vocabulary ) -> [Int]
classifyNaiveBayes test_data trainedModel =
    let vocab = snd trainedModel
        xTest = (NLA.toLists (myVectorizer vocab (test_data)))
        test_len = length xTest
        y = NLA.fromLists [(replicate (test_len) (int2Double 0))]
        -- [Double]
        xgivenY_src = fst (snd (fst trainedModel))
        xgivenY_lang = snd (snd (fst trainedModel))
        prob_src_prior = fst (fst trainedModel)
        log_src = map log xgivenY_src
        log_lang = map log xgivenY_lang
        log_matrix = NLA.tr (NLA.fromLists [log_src, log_lang])
        -- (head (DM.toLists log_matrix)) :: [Double,Double]
        -- matrix mult
        prob1 = (NLA.fromLists xTest) NLA.<> (log_matrix)
        -- (head (DM.toLists prob1))) :: [Double,Double]
        logp = log prob_src_prior
        log_not_p = log (1 - prob_src_prior)
        prob1_trans = NLA.toLists (NLA.tr prob1)
        prob2 = map (\x -> x + logp) (head prob1_trans)
        prob3 = map (\x -> x + log_not_p) (head (tail prob1_trans))
        combined = [prob2, prob3]
        combined_mat = NLA.tr (NLA.fromLists combined)

        final_probs = map (\x -> if (head x) > (head (tail x)) then 0
        ↪  else 1) (NLA.toLists combined_mat)
    in final_probs
```

Lib.hs : Important Helpers

```
myVectorizer :: Vocabulary -> [Document] -> NLA.Matrix Double
myVectorizer vocab docs
    | vocab == [] = NLA.fromLists [[int2Double 0]] --
    ↪  sinceFromlists doesn't accept empty lists
    | docs == [] = NLA.fromLists [[int2Double 0]]
    | otherwise = NLA.fromLists [matrixRow vocab doc | doc <- docs]

matrixRow :: Vocabulary -> Document -> [Double]
matrixRow vocab doc = [fromMaybe (int2Double 0) (lookup vocab_word
↪  mywordcounts) | vocab_word <- vocab]
where mywordcounts = wordCounts doc

wordCounts :: Document -> [(String, Double)]
wordCounts doc = Data.Map.toList $ fromListWith (+) [(oneword,
↪  int2Double 1) | oneword <- words doc]

sumCols :: NLA.Matrix Double -> [Double]
sumCols matrix = map sum (NLA.toLists (NLA.tr matrix))

calcXGivenY :: Int -> [Double] -> [Double]
calcXGivenY mylen my_cols_sum =  map (\x -> x + 0.001 / int2Double
↪  (mylen) + 0.9 ) my_cols_sum
```

Training Data

Language	LoC	Source
C	1171	Andrej Karpathy's Github
Python	461	Sklearn's Github
Java	201	Jenkins Github

Description	Words & Lines	Source
CS50 Lec1	780 and 37	CS50 Lec1
CS50 Lec6	229 and 11	CS50 Lec6
Python 4 Everybody Text	4910 and 589	Python 4 Everybody Text

Challenges and Mitigations

- After midterm eval, redid project to change from HTML to general text
- Tried implementing HMM but decided on Naïve Bayes
- Poor library support : Started from scratch
- Inefficient `matrix` library : Found efficient `hmatrix`, reducing time from 2.5 min to 2.5 sec in one case

Challenges and Mitigations

- Paucity of appropriately sized training data : created custom small dataset
- Changing libraries and refactoring code

Tooling

- Haskell
- Stack build tool
- Notable Libraries
  - hmatrix
  - hUnit
  - pandoc

Testing

- Unit Testing
  - **`myVectorizer`**
  - **`matrixRow`**
  - **`wordCounts`**
  - **`getWords`**
  - **`getUniqueWords`**

Testing

- End-to-end testing
  - Tested by the evaluation tests
- Performance Testing
  - Time usage
- Functional Testing

Results & Discussions

Results : Evaluation on Test Set

Case	Details of Code Portion
1	Supplied Web Page containing C, Python, Java
2	Assembly Code from the Apollo Guidance Computer
3	SQL Code from this blog
4	Haskell Code from ShellCheck
5	Mix of Python and C Code
6	Java Code
7	Python Code

Results : Evaluation

Case	Precision (Code)	Recall (Code)	Precision (Text)	Recall (Text)
1	0.918	0.975	0.956	0.86
2	0.997	1.0	1.0	0.889
3	0.979	0.92	0.667	0.889
4	0.967	0.93	0.474	0.667
5	0.992	0.89	0.383	0.9
6	0.978	0.986	0.882	0.833
7	0.956	0.869	0.435	0.714

Results : Tests

- **Unit Tests :** All passed successfully
- **Performance Testing**
  - On given source : **1.32 seconds**
  - Text of Frankenstein comprising 75,000 words and 1665 lines : **3.74 seconds**
- **Functional Testing**
  - By nature, can’t achieve 100 % accuracy, but has good performance in meeting requirements and specifications

Discussions

- Surprisingly good performance
- Lightweight in terms of training data and time
- Code metrics better than text metrics
- Output is simply classified, not formatted or parsed
- High accuracy despite small and skewed dataset
- Quality of training and testing datasets need to be analyzed further

Test Case 5 Text Misclassification Example

Predict Text

Predict Code

```
# Predict the class for a given row
def predict(summaries, row):
	probabilities = calculate_class_probabilities(summaries, row)
	best_label, best_prob = None, -1
	for class_value, probability in probabilities.items():
		if best_label is None or probability > best_prob:
			best_prob = probability
			best_label = class_value
	return best_label
```

Limitations

- Granular upto line-level and not token level
- Needs new-line separation
- Will likely have inferior performance compared to heavyweight models
- Comments classified as text and not code

Limitations

- Doesn’t take into account context
- Naïve independence assumption & Bag of Words approach
- Hyperparameters and training size not tuned or optimized
- Datasets Quality

Conclusions

- Developed classifier that
  - Is Lightweight, Interpretable & Simple
  - Has strong results despite assumptions and improper training data
  - Can be used in a unified manner with more complex models, which needs to be further investigated
- Analysis of classified results needed to understand why it’s correctly or incorrectly classifying lines

Extensions and Future Work

- Add context and wider window with n-grams
- Semantic approach to induce newlines or,
- Semantic approach to classify within lines
- Extract knowledge from classifier output

Extensions and Future Work

- Tune hyperparameters like Laplacian constants
- Increase training data size and quality
- Write to Word doc without going through pandoc.readHTML
- User Interface
- More testing and profiling

Demo

References

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Thank you!