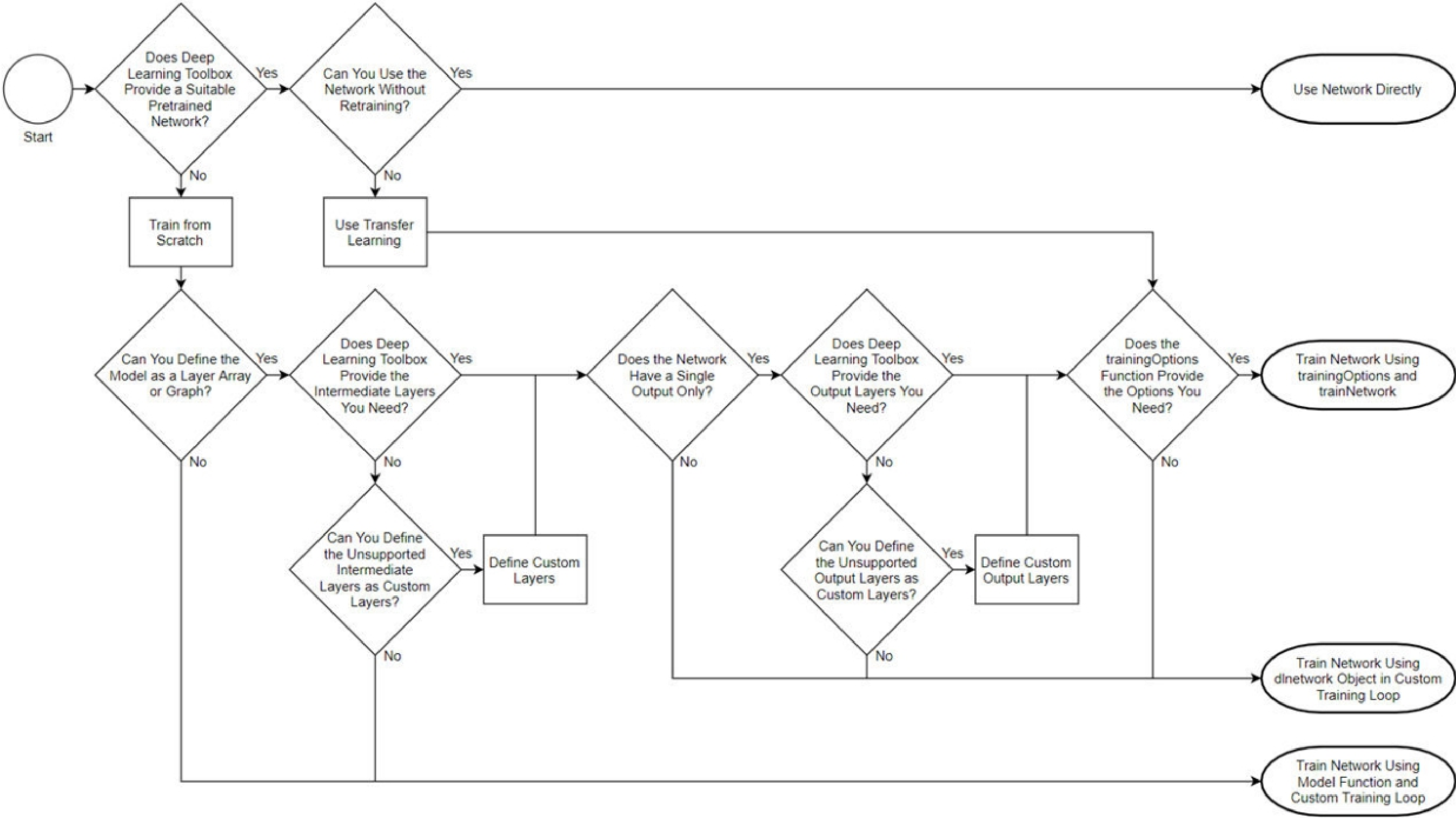
Deep Learning Models for Multilabel Text Classification

- Multilabel Classification with DL Models

Outline

- Multilabel Text Classification Using Deep Learning
  - arXiv API
  - word embedding
  - GRU
  - F-score


Start
Does Deep Learning Toolbox Provide a Suitable Pretrained Network?
Yes
No
Can You Use the Network Without Retraining?
Yes
No
Use Network Directly
Train from Scratch
Use Transfer Learning
Can You Define the Model as a Layer Array or Graph?
Yes
No
Does Deep Learning Toolbox Provide the Intermediate Layers You Need?
Yes
No
Can You Define the Unsupported Intermediate Layers as Custom Layers?
Yes
No
Define Custom Layers
Does the Network Have a Single Output Only?
Yes
No
Does Deep Learning Toolbox Provide the Output Layers You Need?
Yes
No
Can You Define the Unsupported Output Layers as Custom Layers?
Yes
No
Define Custom Output Layers
Does the trainingOptions Function Provide the Options You Need?
Yes
No
Train Network Using trainingOptions and trainNetwork
Train Network Using dlnetwork Object in Custom Training Loop
Train Network Using Model Function and Custom Training Loop

Use network directly

- If a pretrained network already performs the task you require, then you do not need to retrain the network. Instead, you can make predictions with the network directly using the classify and predict functions.

Train network using trainingOptions and trainNetwork

- If you have a network specified as a layer array or layer graph, and the trainingOptions function provides all the options you need, then you can train the network using the trainNetwork function.

Train network using dlnetwork object and custom training loop

- For most tasks, you can control the training algorithm details using the trainingOptions and trainNetwork functions. If the trainingOptions function does not provide the options you need for your task (for example, a custom learn rate schedule), then you can define your own custom training loop using a dlnetwork object. A dlnetwork object allows you to train a network specified as a layer graph using automatic differentiation.
- For loss functions that cannot be specified using an output layer, you can specify the loss in a custom training loop.

Train network using model function and custom training loop

- For networks that cannot be created using layer graphs, you can define custom networks as a function. If parts of the network can be created using a layer graph, then you can define those parts as layer graphs and the unsupported parts using model functions.

Multilabel Text Classification Using Deep Learning

- This example shows how to classify text data that has multiple independent labels. For classification tasks where there can be multiple independent labels for each observation—for example, tags on an scientific article—you can train a deep learning model to predict probabilities for each independent class. To enable a network to learn multilabel classification targets, you can optimize the loss of each class independently using binary cross-entropy loss.

Multilabel Text Classification Using Deep Learning

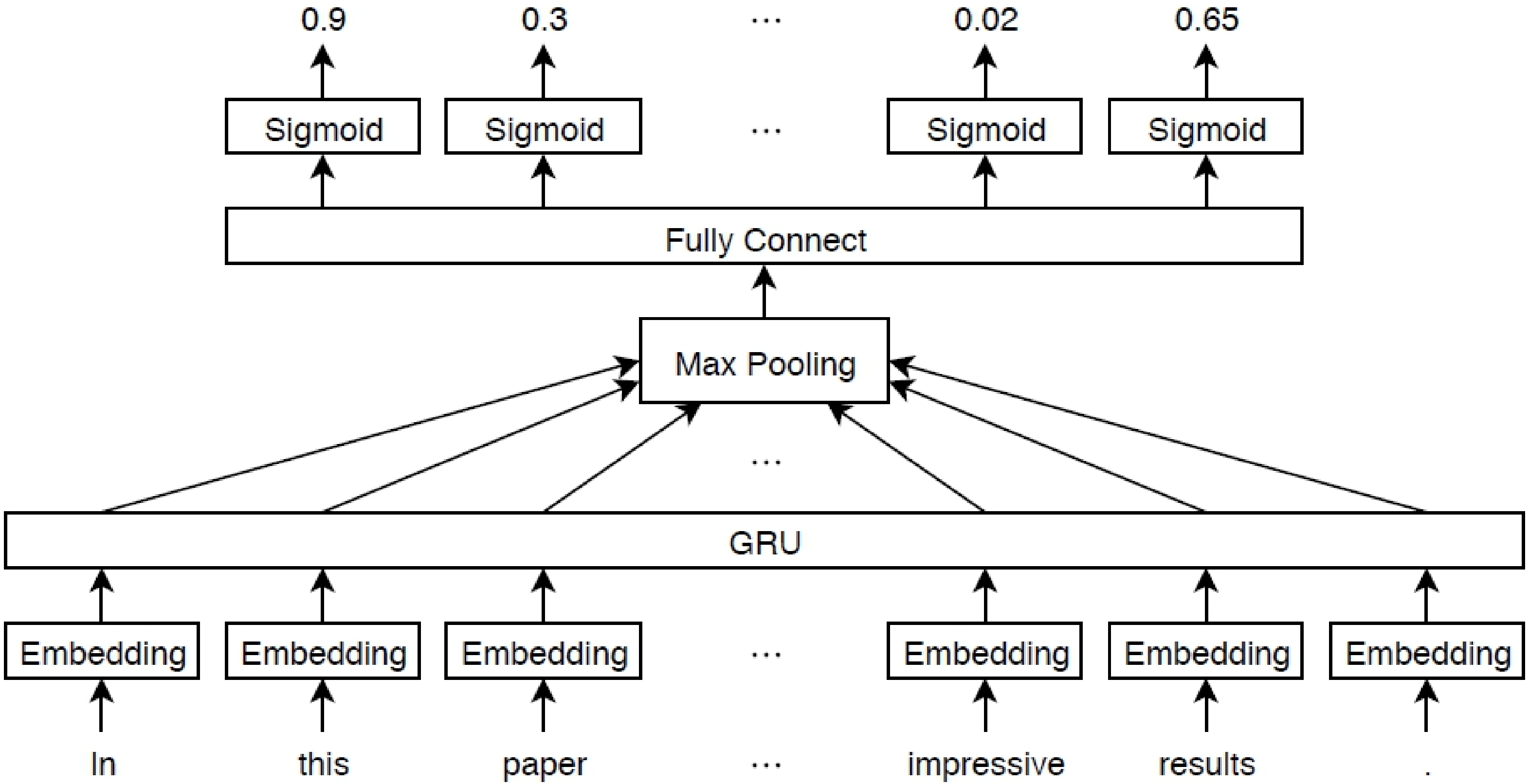
- This example defines a deep learning model that classifies subject areas given the abstracts of computer science papers collected using the arXiv API. The model consists of a word embedding and GRU, max pooling operation, fully connected, and sigmoid operations.
- To measure the performance of multilabel classification, we use the labeling F-score. The labeling F-score evaluates multilabel classification by focusing on per-text classification with partial matches. The measure is the normalized proportion of matching labels against the total number of true and predicted labels.

Multilabel Text Classification Using Deep Learning

This example defines the following model:

- A word embedding that maps a sequence of words to a sequence of numeric vectors.
- A GRU operation that learns dependencies between the embedding vectors.
- A max pooling operation that reduces a sequence of feature vectors to a single feature vector.
- A fully connected layer that maps the features to the binary outputs.
- A sigmoid operation for learning the binary cross entropy loss between the outputs and the target labels.

This diagram shows a piece of text propagating through the model architecture and outputting a vector of probabilities. The probabilities are independent, so they need not sum to one.



Import Text Data

- Import a set of abstracts and category labels from math papers using the arXiv API. Specify the number of records to import using the importSize variable. Note that the arXiv API is rate limited to querying 1000 articles at a time and requires waiting between requests.

```
importSize = 50000;
```

- Import the first set of records.

```
url = "https://export.arxiv.org/oai2?verb=ListRecords" + ...
 "&set=cs" + ...
 "&metadataPrefix=arXiv";
options = weboptions('Timeout',160);
code = webread(url,options);
```

Import Text Data

- Parse the returned XML content and create an array of htmlTree objects containing the record information.

```
tree = htmlTree(code);
subtrees = findElement(tree,"record");
numel(subtrees)
```

Import Text Data

- Iteratively import more chunks of records until the required amount is reached, or there are no more records. To continue importing records from where you left of, use the resumptionToken attribute from the previous result. To adhere to the rate limits imposed by the arXiV API, add a delay of 20 seconds before each query using the pause function.

```
while numel(subtrees) < importSize
  subtreeResumption = findElement(tree,"resumptionToken");
  if isempty(subtreeResumption)
    break
  end
  resumptionToken = extractHTMLText(subtreeResumption);
  url = "https://export.arxiv.org/oai2?verb=ListRecords" + ...
  "&resumptionToken=" + resumptionToken;
  pause(20)
  code = webread(url,options);
  tree = htmlTree(code);
  subtrees = [subtrees; findElement(tree,"record")];
end
```

Extract and Preprocess Text Data

- Extract the abstracts and labels from the parsed HTML trees. Find the "<abstract>" and "<categories>" elements using the findElement function.

```
subtreeAbstract = htmlTree("");
subtreeCategory = htmlTree("");
for i = 1:numel(subtrees)
  subtreeAbstract(i) = findElement(subtrees(i),"abstract");
  subtreeCategory(i) = findElement(subtrees(i),"categories");
end
```

Extract and Preprocess Text Data

- Extract the text data from the subtrees containing the abstracts using the extractHTMLText function.

```
textData = extractHTMLText(subtreeAbstract);
```

- Tokenize and preprocess the text data using the preprocessText function.

```
documentsAll = preprocessText(textData);
documentsAll(1:5)
ans =
 5×1 tokenizedDocument:
   72 tokens: describe new algorithm $(k,\ell)$ pebble game color obtain ......
```

Extract and Preprocess Text Data

- Extract the labels from the subtrees containing the labels.

```
strLabels = extractHTMLText(subtreeCategory);
labelsAll = arrayfun(@split,strLabels,'UniformOutput',false);
```

- Remove labels that do not belong to the "cs" set.

```
for i = 1:numel(labelsAll)
   labelsAll{i} = labelsAll{i}(startsWith(labelsAll{i},"cs."));
end
```

Extract and Preprocess Text Data

Visualize some of the classes in a word cloud. Find the documents corresponding to the following:

- Abstracts tagged with "Artificial Intelligence" and not tagged with "Computer Vision"
- Abstracts tagged with "Computer Vision" and not tagged with "Artificial Intelligence"
- Abstracts tagged with both "Combinatorics" and "Computer Vision"

Extract and Preprocess Text Data

- Find the document indices for each of the groups using the ismember function.

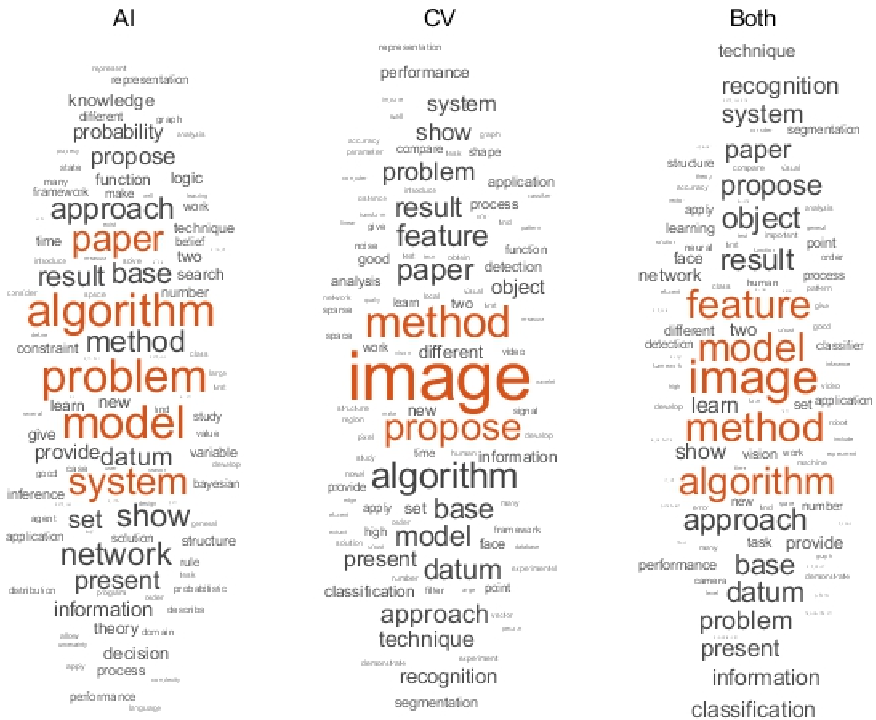
```
idxAI = cellfun(@(lbls) ismember("cs.AI",lbls) &&
~ismember("cs.CV",lbls),labelsAll);
idxCV = cellfun(@(lbls) ismember("cs.CV",lbls) &&
~ismember("cs.AI",lbls),labelsAll);
idxAICV = cellfun(@(lbls) ismember("cs.AI",lbls) &&
ismember("cs.CV",lbls),labelsAll);
```

Extract and Preprocess Text Data

```
figure
subplot(1,3,1)
wordcloud(documentsAll(idxAI));
title("AI")

subplot(1,3,2)
wordcloud(documentsAll(idxCV));
title("CV")

subplot(1,3,3)
wordcloud(documentsAll(idxAICV));
title("Both")
```



Extract and Preprocess Text Data

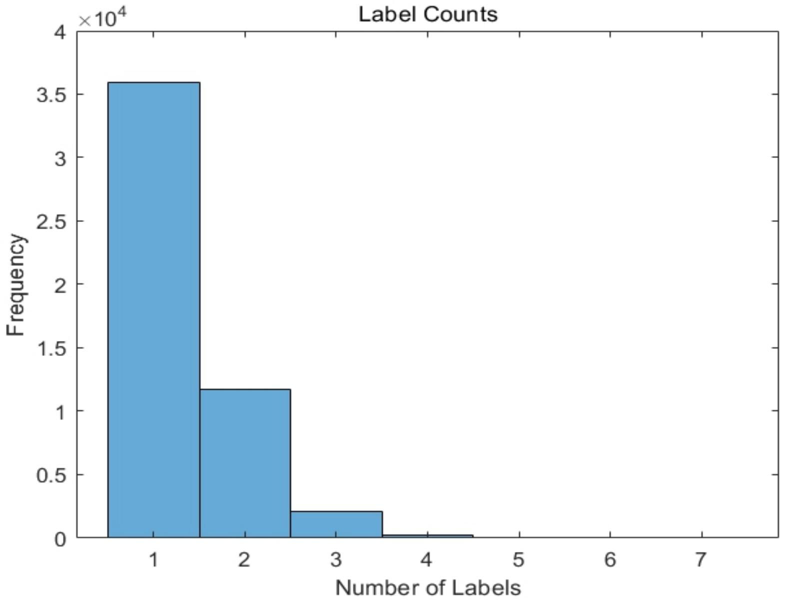
- View the number of classes.

```
classNames = unique(cat(1,labelsAll{:}));
numClasses = numel(classNames)
% numClasses = 40
```

Extract and Preprocess Text Data

- Visualize the number of per-document labels using a histogram.

```
labelCounts = cellfun(@numel, labelsAll);
figure
histogram(labelCounts)
xlabel("Number of Labels")
ylabel("Frequency")
title("Label Counts")
```



Prepare Text Data for Deep Learning

- Partition the data into training and validation partitions using the cvpartition function. Hold out 10% of the data for validation by setting the 'HoldOut' option to 0.1.

```
cvp = cvpartition(numel(documentsAll),'HoldOut',0.1);
documentsTrain = documentsAll(training(cvp));
documentsValidation = documentsAll(test(cvp));
labelsTrain = labelsAll(training(cvp));
labelsValidation = labelsAll(test(cvp));
```

Prepare Text Data for Deep Learning

- Create a word encoding object that encodes the training documents as sequences of word indices. Specify a vocabulary of the 5000 words by setting the 'Order' option to 'frequency', and the 'MaxNumWords' option to 5000.

```
enc = wordEncoding(documentsTrain,'Order','frequency','MaxNumWords',5000)
enc =
 wordEncoding with properties:
 NumWords: 5000
 Vocabulary: [1×5000 string]
```

Prepare Text Data for Deep Learning

To improve training, use the following techniques:

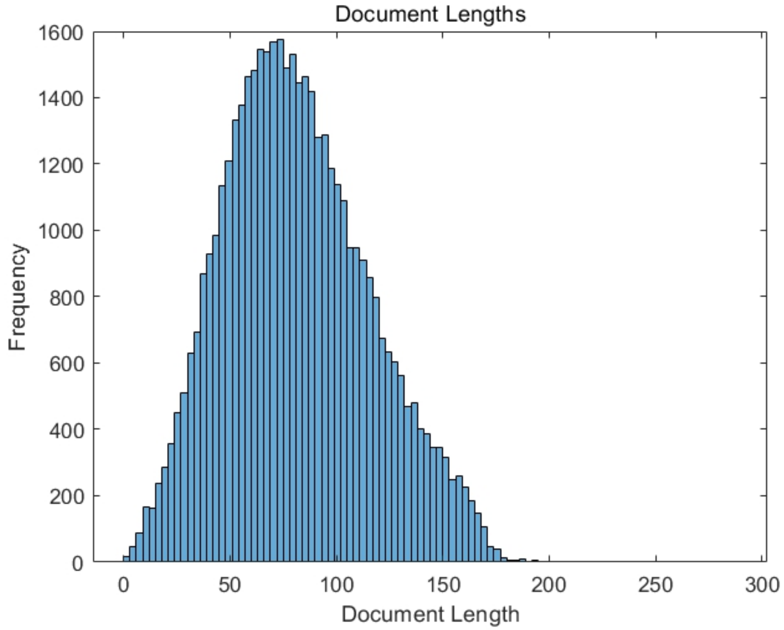
1: When training, truncate the documents to a length that reduces the amount of padding used and does not does discard too much data.

2: Train for one epoch with the documents sorted by length in ascending order, then shuffle the data each epoch. This technique is known as sortagrad.

Prepare Text Data for Deep Learning

- To choose a sequence length for truncation, visualize the document lengths in a histogram and choose a value that captures most of the data.

```
documentLengths = doclength(documentsTrain);
figure
histogram(documentLengths)
xlabel("Document Length")
ylabel("Frequency")
title("Document Lengths")
```



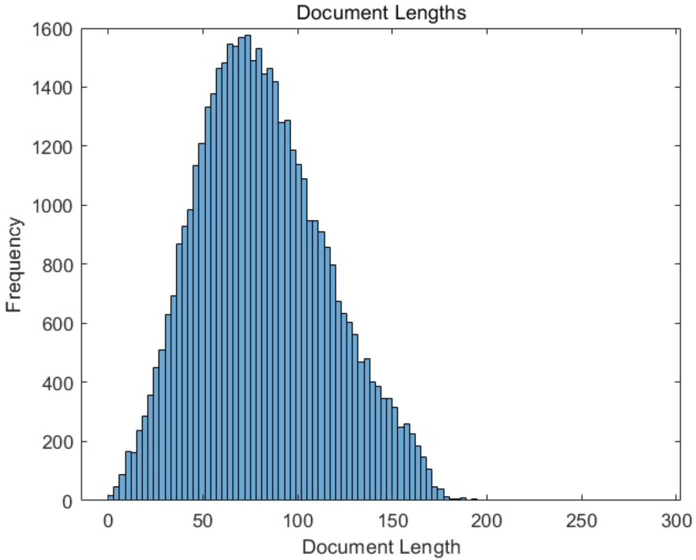
Prepare Text Data for Deep Learning

- Most of the training documents have fewer than 175 tokens. Use 175 tokens as the target length for truncation and padding.

```
maxSequenceLength = 175;
```

- To use the sortagrad technique, sort the documents by length in ascending order.

```
[~,idx] = sort(documentLengths);
documentsTrain = documentsTrain(idx);
labelsTrain = labelsTrain(idx);
```



Define and Initialize Model Parameters

- Define the parameters for each of the operations and include them in a struct. Use the format parameters.OperationName.ParameterName, where parameters is the struct, OperationName is the name of the operation (for example "fc"), and ParameterName is the name of the parameter (for example, "Weights").

Define and Initialize Model Parameters

Create a struct parameters containing the model parameters. Initialize the bias with zeros. Use the following weight initializers for the operations:

- For the embedding, initialize the weights with random normal values.
- For the GRU operation, initialize the weights using the initializeGlorot function.
- For the fully connect operation, initialize the weights using the initializeGaussian function.

Define and Initialize Model Parameters

```
embeddingDimension = 300;
numHiddenUnits = 250;
inputSize = enc.NumWords + 1;
parameters = struct;
parameters.emb.Weights = dlarray(randn([embeddingDimension inputSize]));
parameters.gru.InputWeights =
dlarray(initializeGlorot(3*numHiddenUnits,embeddingDimension));
parameters.gru.RecurrentWeights =
dlarray(initializeGlorot(3*numHiddenUnits,numHiddenUnits));
parameters.gru.Bias = dlarray(zeros(3*numHiddenUnits,1,'single'));
parameters.fc.Weights = dlarray(initializeGaussian([numClasses,numHiddenUnits]));
parameters.fc.Bias = dlarray(zeros(numClasses,1,'single'));
```

Define and Initialize Model Parameters

- View the parameters struct.

parameters

parameters = struct with fields:

emb: [1×1 struct]

gru: [1×1 struct]

fc: [1×1 struct]

Define and Initialize Model Parameters

- View the parameters for the GRU operation.

parameters.gru

ans = struct with fields:

InputWeights: [750×300 dlarray]

RecurrentWeights: [750×250 dlarray]

Bias: [750×1 dlarray]

Define Model Function

- Create the function model, which computes the outputs of the deep learning model described earlier. The function model takes as input the input data *dlX* and the model parameters *parameters*. The network outputs the predictions for the labels.

Define Model Gradients Function

- Create the function modelGradients, which takes as input a mini-batch of input data *dlX* and the corresponding targets *T* containing the labels, and returns the gradients of the loss with respect to the learnable parameters, the corresponding loss, and the network outputs.

Specify Training Options

- Train for 5 epochs with a mini-batch size of 256.

```
numEpochs = 5;
miniBatchSize = 256;
```

- Train using the Adam optimizer, with a learning rate of 0.01, and specify gradient decay and squared gradient decay factors of 0.5 and 0.999, respectively.

```
learnRate = 0.01;
gradientDecayFactor = 0.5;
squaredGradientDecayFactor = 0.999;
```

Specify Training Options

- Clip the gradients with a threshold of 1 using L2 norm gradient clipping.

```
gradientThreshold = 1;
```

- Visualize the training progress in a plot.

```
plots = "training-progress";
```

- To convert a vector of probabilities to labels, use the labels with probabilities higher than a specified threshold. Specify a label threshold of 0.5.

```
labelThreshold = 0.5;
```

Specify Training Options

- Validate the network every epoch.

```
numObservationsTrain = numel(documentsTrain);
numIterationsPerEpoch = floor(numObservationsTrain/miniBatchSize);
validationFrequency = numIterationsPerEpoch;
```

- Train on a GPU if one is available.

```
executionEnvironment = "auto";
```

Train Model

Train the model using a custom training loop.

- For each epoch, loop over mini-batches of data. At the end of each epoch, shuffle the data. At the end of each iteration, update the training progress plot.

For each mini-batch:

• Convert the documents to sequences of word indices and convert the labels to dummy variables.

• Convert the sequences to dlarray objects with underlying type single and specify the dimension labels 'BCT' (batch, channel, time).

Train Model

- For GPU training, convert to gpuArray objects.
- Evaluate the model gradients and loss using dlfeval and the modelGradients function.
- Clip the gradients.
- Update the network parameters using the adamupdate function.
- If necessary, validate the network using the modelPredictions function, listed at the end of the example.
- Update the training plot.

```
if plots == "training-progress"
  figure
  % Labeling F-Score.
  subplot(2,1,1)
  lineFScoreTrain = animatedline('Color',[0 0.447 0.741]);
  lineFScoreValidation = animatedline('LineStyle','--',  'Marker','o', 'MarkerFaceColor','black');
  ylim([0 1]);   xlabel("Iteration");   ylabel("Labeling F-Score")
  grid on
  % Loss.
  subplot(2,1,2)
  lineLossTrain = animatedline('Color',[0.85 0.325 0.098]);
  lineLossValidation = animatedline('LineStyle','--', 'Marker','o', 'MarkerFaceColor','black');
  ylim([0 inf]);   xlabel("Iteration");   ylabel("Loss")
  grid on
end
```

- Initialize parameters for the Adam optimizer.

```
trailingAvg = [];
trailingAvgSq = [];
```

- Prepare the validation data. Create a one-hot encoded matrix where non-zero entries correspond to the labels of each observation.

```
numObservationsValidation = numel(documentsValidation);
TValidation = zeros(numClasses, numObservationsValidation, 'single');
for i = 1:numObservationsValidation
   [~,idx] = ismember(labelsValidation{i},classNames);
   TValidation(idx,i) = 1;
end
```

- Train the model.

```
iteration = 0;
start = tic;
% Loop over epochs.
for epoch = 1:numEpochs

 % Loop over mini-batches.
 for i = 1:numIterationsPerEpoch
 iteration = iteration + 1;
 idx = (i-1)*miniBatchSize+1:i*miniBatchSize;

 % Read mini-batch of data and convert the labels to dummy
 % variables.
 documents = documentsTrain(idx);
 labels = labelsTrain(idx);
```

```
% Convert documents to sequences.
len = min(maxSequenceLength,max(doclength(documents)));
X = doc2sequence(enc,documents, ...
'PaddingValue',inputSize, ...
'Length',len);
X = cat(1,X{:});
% Dummify labels.
T = zeros(numClasses, miniBatchSize, 'single');
for j = 1:miniBatchSize
[~,idx2] = ismember(labels{j},classNames);
T(idx2,j) = 1;
end

% Convert mini-batch of data to dlarray.
dlX = dlarray(X,'BTC');
```

```
% If training on a GPU, then convert data to gpuArray.
if (executionEnvironment == "auto" && canUseGPU) || executionEnvironment == "gpu"
dlX = gpuArray(dlX);
end
% Evaluate the model gradients, state, and loss using dlfeval and the
% modelGradients function.
[gradients,loss,dlYPred] = dlfeval(@modelGradients, dlX, T, parameters);

% Gradient clipping.
gradients = dlupdate(@(g) thresholdL2Norm(g, gradientThreshold),gradients);

% Update the network parameters using the Adam optimizer.
[parameters,trailingAvg,trailingAvgSq] = adamupdate(parameters,gradients, ...
trailingAvg,trailingAvgSq,iteration,learnRate,gradientDecayFactor,squaredGradientDecayFactor);
```

```
if plots == "training-progress"
 subplot(2,1,1)
 D = duration(0,0,toc(start),'Format','hh:mm:ss');
 title("Epoch: " + epoch + ", Elapsed: " + string(D))

 % Loss.
 addpoints(lineLossTrain,iteration,double(gather(extractdata(loss))))

 % Labeling F-score.
 YPred = extractdata(dlYPred) > labelThreshold;
 score = labelingFScore(YPred,T);
 addpoints(lineFScoreTrain,iteration,double(gather(score)))

 drawnow
```

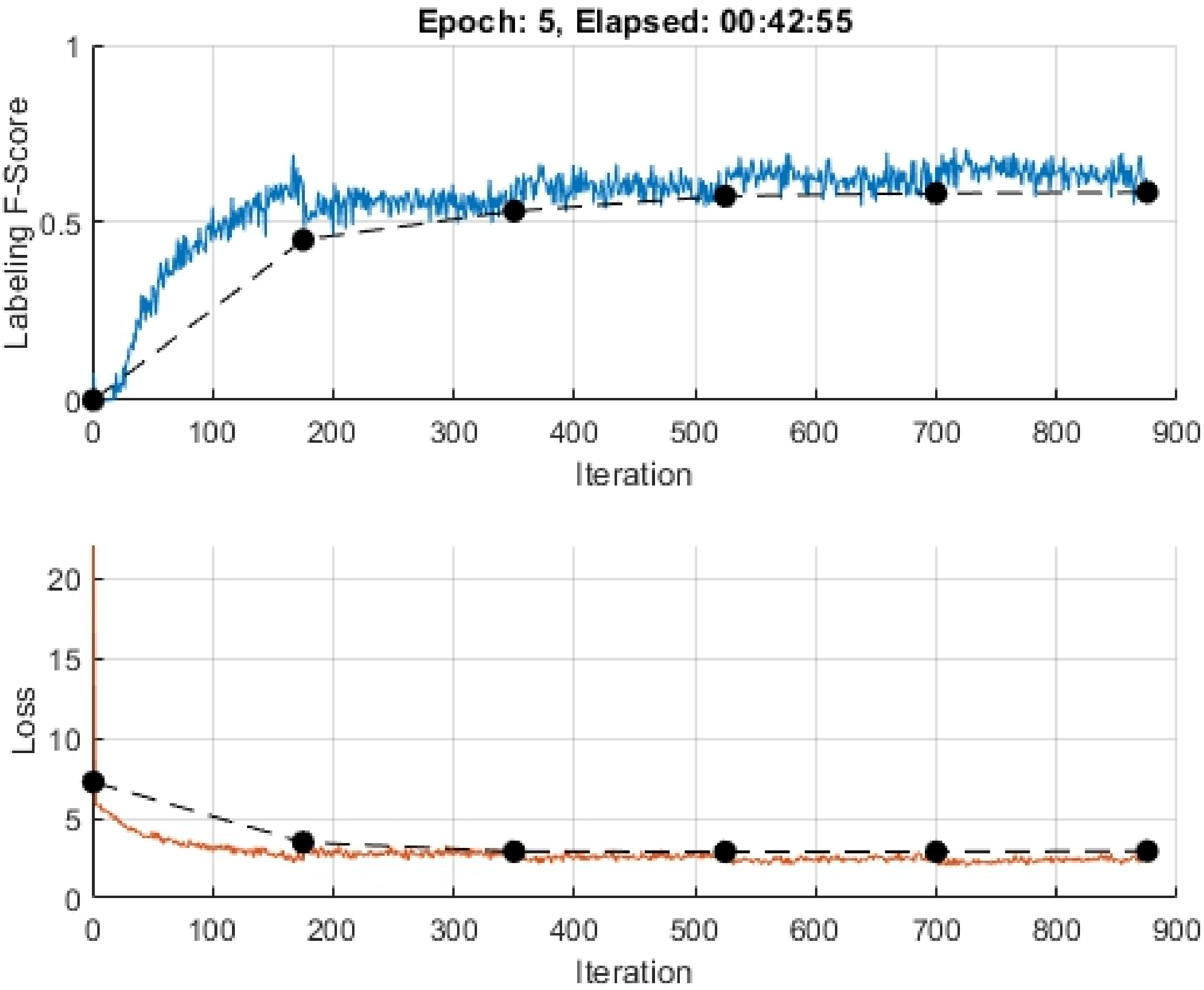
```
% Display validation metrics.
if iteration == 1 || mod(iteration,validationFrequency) == 0
dlYPredValidation =
modelPredictions(parameters,enc,documentsValidation,miniBatchSize,maxSequenceLength);

% Loss.
lossValidation = crossentropy(dlYPredValidation,TValidation, ...
'TargetCategories','independent', ...
'DataFormat','CB');
addpoints(lineLossValidation,iteration,double(gather(extractdata(lossValidation))))

% Labeling F-score.
YPredValidation = extractdata(dlYPredValidation) > labelThreshold;
score = labelingFScore(YPredValidation,TValidation);
addpoints(lineFScoreValidation,iteration,double(gather(score)))
```

```
        end
      end
    end

    % Shuffle data.
    idx = randperm(numObservationsTrain);
    documentsTrain = documentsTrain(idx);
    labelsTrain = labelsTrain(idx);
end
```


Epoch: 5, Elapsed: 00:42:55
Labeling F-Score
Iteration
Loss
Iteration

Test Model

- To make predictions on a new set of data, use the modelPredictions function. The modelPredictions function takes as input the model parameters, a word encoding, and an array of tokenized documents, and outputs the model predictions corresponding to the specified mini-batch size and the maximum sequence length.

```
dlYPredValidation = modelPredictions(parameters,enc,documentsValidation,miniBatchSize,maxSequenceLength);
```

Test Model

- To convert the network outputs to an array of labels, find the labels with scores higher than the specified label threshold.

YPredValidation = extractdata(dlYPredValidation) > labelThreshold;

- To evaluate the performance, calculate the labeling F-score using the labelingFScore function. The labeling F-score evaluates multilabel classification by focusing on per-text classification with partial matches.

score = labelingFScore(YPredValidation,TValidation)

score = single

0.5852

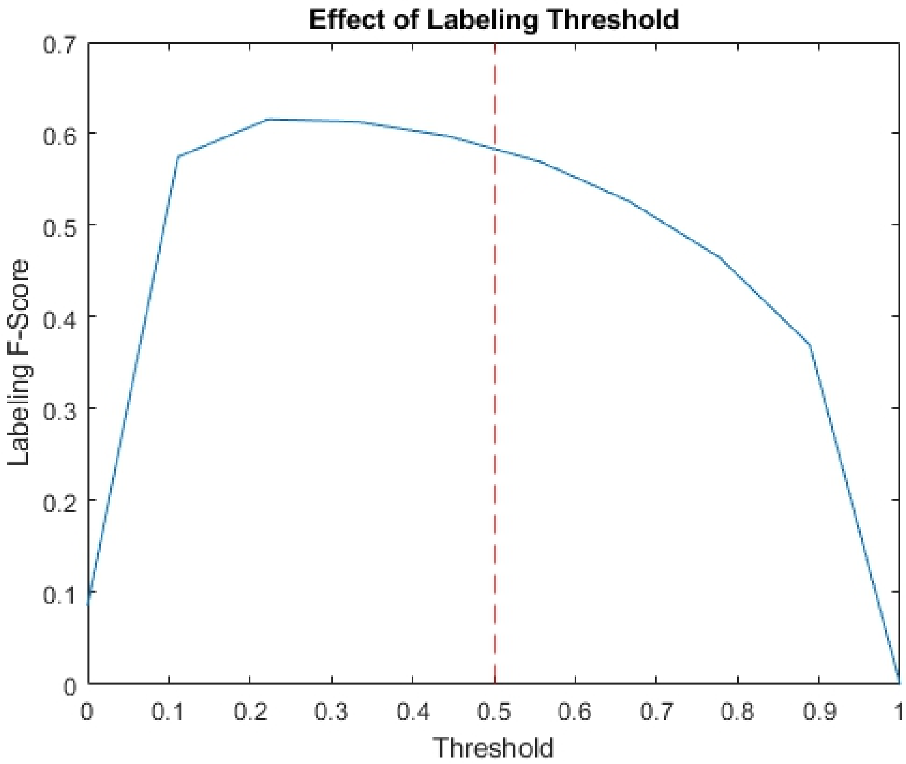
Test Model

- View the effect of the labeling threshold on the labeling F-score by trying a range of values for the threshold and comparing the results.

```
thr = linspace(0,1,10);
score = zeros(size(thr));
for i = 1:numel(thr)
   YPredValidationThr = extractdata(dlYPredValidation) >= thr(i);
   score(i) = labelingFScore(YPredValidationThr,TValidation);
end
```

Test Model

```
figure
plot(thr,score)
xline(labelThreshold,'r--');
xlabel("Threshold")
ylabel("Labeling F-Score")
title("Effect of Labeling Threshold")
```



Visualize Predictions

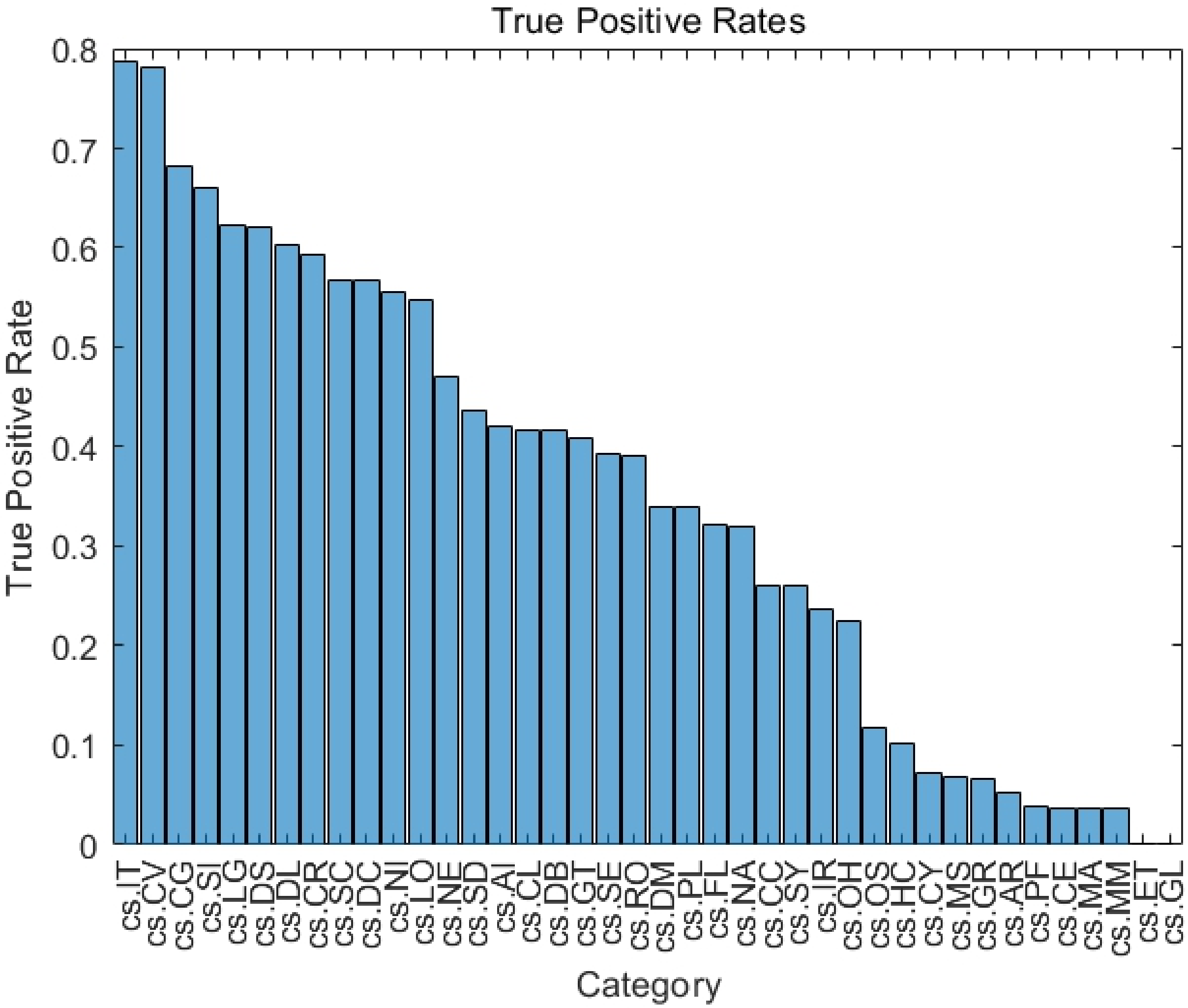
- To visualize the correct predictions of the classifier, calculate the numbers of true positives. A true positive is an instance of a classifier correctly predicting a particular class for an observation.

```
Y = YPredValidation;
T = TValidation;
numTruePositives = sum(T & Y,2);
numObservationsPerClass = sum(T,2);
truePositiveRates = numTruePositives ./ numObservationsPerClass;
```

Visualize Predictions

- Visualize the numbers of true positives for each class in a histogram.

```
figure
[~,idx] = sort(truePositiveRates,'descend');
histogram('Categories',classNames(idx),'BinCounts',truePositiveRates(idx))
xlabel("Category")
ylabel("True Positive Rate")
title("True Positive Rates")
```



True Positive Rates
True Positive Rate
Category
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
cs.IT
cs.CV
cs.CG
cs.SI
cs.LG
cs.DS
cs.DL
cs.CR
cs.SC
cs.DC
cs.NI
cs.LO
cs.NE
cs.SD
cs.AI
cs.CL
cs.DB
cs.GT
cs.SE
cs.RO
cs.DM
cs.PL
cs.FL
cs.NA
cs.CC
cs.SY
cs.IR
cs.OH
cs.OS
cs.HC
cs.CY
cs.MS
cs.GR
cs.AR
cs.PF
cs.CE
cs.MA
cs.MM
cs.ET
cs.GL

Visualize Predictions

- Visualize the instances where the classifier predicts incorrectly by showing the distribution of true positives, false positives, and false negatives. A false positive is an instance of a classifier assigning a particular incorrect class to an observation. A false negative is an instance of a classifier failing to assign a particular correct class to an observation.

Visualize Predictions

Create a confusion matrix showing the true positive, false positive, and false negative counts:

- For each class, display the true positive counts on the diagonal.
- For each pair of classes (i,j), display the number of instances of a false positive for j when the instance is also a false negative for i.

Visualize Predictions

Create a confusion matrix showing the true positive, false positive, and false negative counts:

- For each class, display the true positive counts on the diagonal.
- For each pair of classes (i,j), display the number of instances of a false positive for j when the instance is also a false negative for i.

That is, the confusion matrix with elements given by:

$$TPFN_{i\,j} = \begin{cases} \text{numTruePositives}(i), \text{ if } i = j \\ \text{numFalsePositives}(j \mid i \text{ is a false negative}), \text{ if } i \neq j \end{cases}$$

Visualize Predictions

- Calculate the false negatives and false positives.

```
falseNegatives = T & ~Y;
falsePositives = ~T & Y;
```

- Calculate the off-diagonal elements.

```
falseNegatives = permute(falseNegatives,[3 2 1]);
numConditionalFalsePositives = sum(falseNegatives & falsePositives, 2);
numConditionalFalsePositives = squeeze(numConditionalFalsePositives);
tpfnMatrix = numConditionalFalsePositives;
```

Visualize Predictions

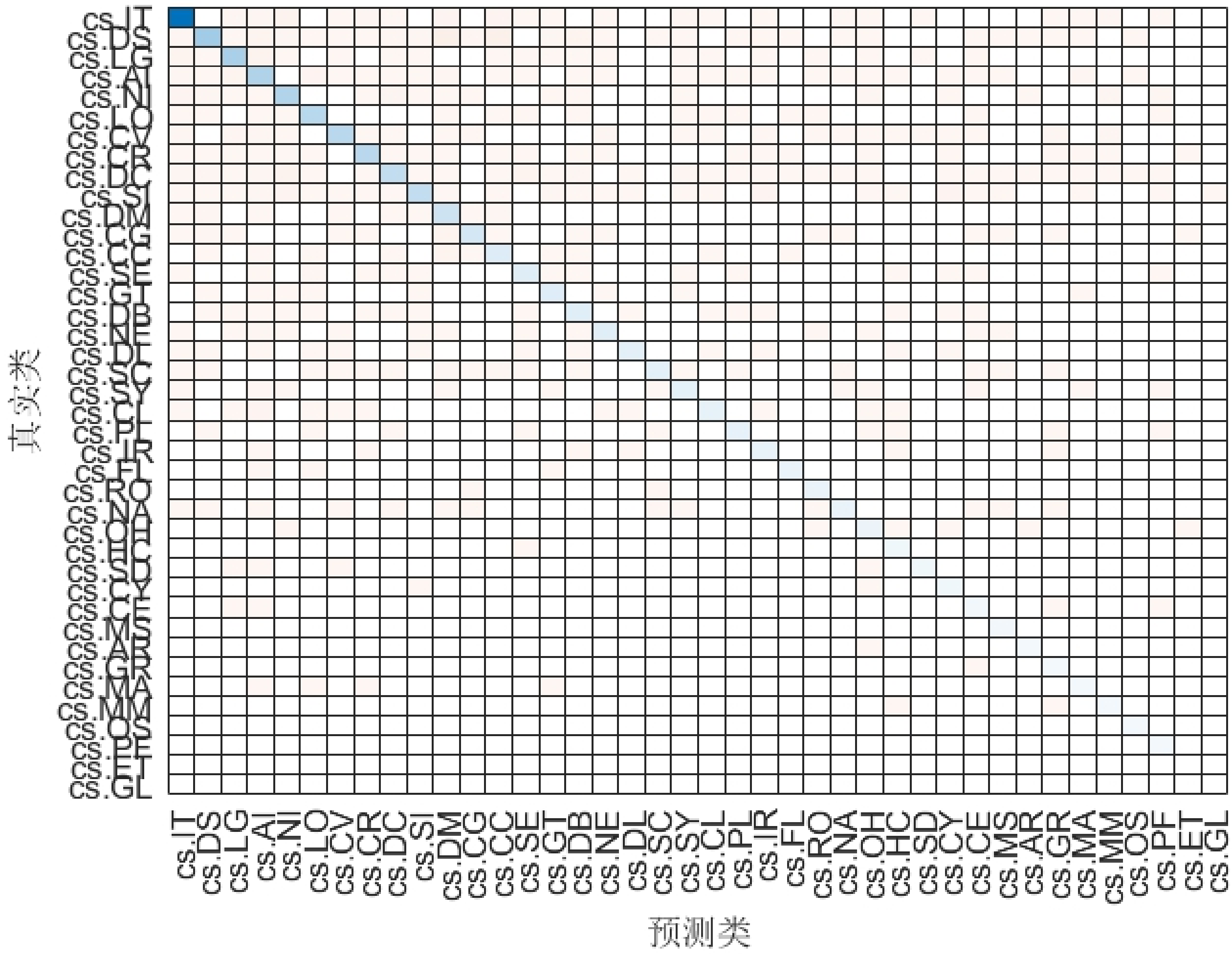
- Set the diagonal elements to the true positive counts.

```
idxDiagonal = 1:numClasses+1:numClasses^2;
tpfnMatrix(idxDiagonal) = numTruePositives;
```

- Visualize the true positive and false positive counts in a confusion matrix using the confusionchart function and sort the matrix such that the elements on the diagonal are in descending order.

```
figure
cm = confusionchart(tpfnMatrix,classNames);
sortClasses(cm,"descending-diagonal");
title("True Positives, False Positives")
```

True Positives, False Positives



Preprocess Text Function

```
function documents = preprocessText(textData)
% Tokenize the text.
regularExpressions = table;
regularExpressions.Pattern = "\$.*?\$";
regularExpressions.Type = "equation";
documents = tokenizedDocument(textData,'RegularExpressions',regularExpressions);
% Erase punctuation.
documents = erasePunctuation(documents);
% Convert to lowercase.
documents = lower(documents);
```

Preprocess Text Function

```
% Lemmatize.
documents = addPartOfSpeechDetails(documents);
documents = normalizeWords(documents,'Style','Lemma');
% Remove stop words.
documents = removeStopWords(documents);
% Remove short words.
documents = removeShortWords(documents,2);
end
```

Model Function

- The function model takes as input the input data dlX and the model parameters parameters, and returns the predictions for the labels.

```
function dlY = model(dlX,parameters)
% Embedding
weights = parameters.emb.Weights;
dlX = embedding(dlX, weights);
% GRU
inputWeights = parameters.gru.InputWeights;
recurrentWeights = parameters.gru.RecurrentWeights;
bias = parameters.gru.Bias;
numHiddenUnits = size(inputWeights,1)/3;
hiddenState = dlarray(zeros([numHiddenUnits 1]));
```

Model Function

```
dlY = gru(dlX, hiddenState, inputWeights, recurrentWeights, bias,'DataFormat','CBT');
% Max pooling along time dimension
dlY = max(dlY,[],3);
% Fully connect
weights = parameters.fc.Weights;
bias = parameters.fc.Bias;
dlY = fullyconnect(dlY,weights,bias,'DataFormat','CB');
% Sigmoid
dlY = sigmoid(dlY);
end
```

Model Gradients Function

- The modelGradients function takes as input a mini-batch of input data dlX with corresponding targets T containing the labels and returns the gradients of the loss with respect to the learnable parameters, the corresponding loss, and the network outputs.

```
function [gradients,loss,dlYPred] = modelGradients(dlX,T,parameters)
dlYPred = model(dlX,parameters);
loss = crossentropy(dlYPred,T,'TargetCategories','independent','DataFormat','CB');
gradients = dlgradient(loss,parameters);
end
```

Model Predictions Function

- The modelPredictions function takes as input the model parameters, a word encoding, an array of tokenized documents, a mini-batch size, and a maximum sequence length, and returns the model predictions by iterating over mini-batches of the specified size.

```
function dlYPred = modelPredictions(parameters,enc,documents,miniBatchSize,maxSequenceLength)
inputSize = enc.NumWords + 1;
numObservations = numel(documents);
numIterations = ceil(numObservations / miniBatchSize);
numFeatures = size(parameters.fc.Weights,1);
dlYPred = zeros(numFeatures,numObservations,'like',parameters.fc.Weights);
```

Model Predictions Function

```
for i = 1:numIterations
 idx = (i-1)*miniBatchSize+1:min(i*miniBatchSize,numObservations);
 len = min(maxSequenceLength,max(doclength(documents(idx))));
 X = doc2sequence(enc,documents(idx), ...
 'PaddingValue',inputSize, ...
 'Length',len);
 X = cat(1,X{:});

 dlX = dlarray(X,'BTC');
 dlYPred(:,idx) = model(dlX,parameters);
end
end
```

Labeling F-Score Function

- The labeling F-score function evaluates multilabel classification by focusing on per-text classification with partial matches. The measure is the normalized proportion of matching labels against the total number of true and predicted labels given by

$$\frac{1}{N}\sum_{n=1}^{N}\left(\frac{2\sum_{c=1}^{C} Y_{nc}T_{nc}}{\sum_{c=1}^{C}(Y_{nc}+T_{nc})}\right),$$

- where N and C correspond to the number of observations and classes, respectively, and Y and T correspond to the predictions and targets, respectively.

```
function score = labelingFScore(Y,T)
  numObservations = size(T,2);
  scores = (2 * sum(Y .* T)) ./ sum(Y + T);
  score = sum(scores) / numObservations;
end
```

Embedding Function

- The embedding function maps numeric indices to the corresponding vector given by the input weights.

```
function Z = embedding(X, weights)
% Reshape inputs into a vector.
[N, T] = size(X, 2:3);
X = reshape(X, N*T, 1);
% Index into embedding matrix.
Z = weights(:, X);
% Reshape outputs by separating batch and sequence dimensions.
Z = reshape(Z, [], N, T);
end
```

L_2 Norm Gradient Clipping Function

- The thresholdL2Norm function scales the input gradients so that their L2 norm values equal the specified gradient threshold when the L2 norm value of the gradient of a learnable parameter is larger than the specified threshold.

```
function gradients = thresholdL2Norm(gradients,gradientThreshold)
    gradientNorm = sqrt(sum(gradients(:).^2));
    if gradientNorm > gradientThreshold
        gradients = gradients * (gradientThreshold / gradientNorm);
    end
end
```