Deep Learning in Personalization: Developing a retail customer use case

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agenda

- Objective
- Recommendations Engines
- Wide and Deep Example in Intel® nGraph™
  - Use Case
  - Data
  - Model
  - Text and Image data
- Evaluation Metric
- Results
- Call to Action
Objective

- This session will develop a Deep Learning Recommender System based on Wide and Deep model and Retail data.
- This exercise starts from scratch using Intel® nGraph™. We will see a series of code snippets that describes core elements in order to build a Recommender System using Deep Learning.
- Will also present different techniques to incorporate other information when available into the model.
- Finally will show results indicating how DL techniques are performing better than traditional ML techniques in this particular use case.
INTEL ngraph

http://ngraph.nervanasys.com/docs/latest/install.html
Recommendations engines

- Classic Collaborative Filtering Approaches.
  - User – Item: The similarity between users to score the items' relevance.
  - Item – Item: The similarity between items to score their relevance for the user.
- Non-negative factorization: A matrix factorization technique to solve the usual sparse nature of recommendations.

https://github.com/NervanaSystems/ngraph-python/tree/master/examples/wide_dee
https://www.tensorflow.org/tutorials/wide_and_deep
Use case

• Data
• Customer Identifiers: Credit Card and Name.
• Transaction Data: Date, Item, Amount.
• Transaction data as an indirect signal for preference.
• Normalization.
• Unique mapping.
# Defining the columns.
COLUMNS = ["Item Id", "Quantity Sold", "Loyalty Customer Name"]

# Reading the data.
dataSales = pd.read_csv("Sales.csv", usecols=COLUMNS, engine="python")

# Analyze your data and process it accordingly.
# Example of Filtering
dataSales = dataSales[dataSales["Quantity Sold"] < 500.0]

# Normalize Columns Individually in Pandas data frame between [0,1]
from sklearn import preprocessing
def normalize(df):
    min_max_scaler = preprocessing.MinMaxScaler()
    df_scaled = min_max_scaler.fit_transform(df.values)
    df_normalized = pd.DataFrame(df_scaled)
    return df_normalized
Data: pandas / SKlearn

- # Unique Mapping
- UID = "Loyalty Customer Name"
- ItemID = "Item id"

nCustomers = 0
customerDict = {}

nItems = 0
itemDict = {}

for index, row in dataSales.iterrows():
    if row[UID] not in customerDict.keys():
        customerDict[UID]=nCustomers
        nCustomers+=1
    if row[ItemID] not in itemDict.keys():
        itemDict[row[ItemID]] = nItems
        nItems +=1

- dataSales[UID] = dataSales[UID].apply(lambda x: customerDict[x])
- dataSales[ItemID] = dataSales[ItemID].apply(lambda x: itemDict[x])
Model - architecture

- ReLu instead of Sigmoid.
- Removed linear part.
- Deep Hidden Layers
- Embeddings
# Placeholders for the embeddings and the outputs

```python
def make_placeholders(batch_size, parameters):
    placeholders = {}
    placeholders['N'] = ng.make_axis(length=batch_size, name='N')
    placeholders['Y'] = ng.placeholder(axes=[placeholders['N']], name="Y")

    embeddings_placeholders = []
    for lut in range(parameters['number_of_embeddings']):
        embedding_placeholder = ng.placeholder(ng.make_axes([placeholders['N']]), name="EMB")
        embeddings_placeholders.append(embedding_placeholder)

    placeholders['embeddings_placeholders'] = embeddings_placeholders

    return placeholders
```
MODEL - Embeddings

- # Embeddings Layers
  # In this case we have 2 embeddings
- # Customers and Items.

- luts = []
  for e in range(parameters['number_of_embeddings']):
    init_uniform = UniformInit(0, 1)
    lut = LookupTable(parameters['tokens_in_embeddings'][e], parameters['dimensions_embeddings'][e], init_uniform, pad_idx=0, update=True)
  
luts.append(lut)
MODEL – Deep model

- # Deep Hidden Layers
- deep_parameters = [32, 16, 16, 8]

```python
layers = []
drop_out_rate = 0.1

for i in range(len(deep_parameters)):
    layers.append(Affine(nout=deep_parameters[i], weight_init=init_xavier, activation=Rectlin()))
    if drop_out_rate > 0.0:
        layers.append(Dropout(keep=drop_out_rate))

layers.append(Affine(axes=tuple(), weight_init=init_xavier))

deep_layers = Sequential(layers)
```
MODEL – building the graph and losses

- # Building the graph
  inputs = make_placeholders(batch_size)

  embedding_ops = []

  for idx, lut in enumerate(luts):
    embedding_op = lut(inputs['embeddings_placeholders'][idx])
    embedding_ops.append(embedding_op)

  X_deep = ng.concat_along_axis(embedding_ops, ng.make_axis(name="F"))

  deep = ng.maximum((deep_layers(X_deep) + ng.variable(), initial_value=0.5).named('b')), 0)

- # RMS
  loss = ng.squared_L2(deep - inputs['Y'])

- # L2 loss for regularization purposes
  loss = ng.sum(loss, out_axes=[])+ng.squared_L2(deep)
Text and Image data

Customer Embedding
Customer Identifier

Product Embedding
Product Identifier

Text Embedding
Text

Bottleneck Features

Deep Convolutional Network
Text data – i/o

- **# Create a new column with embeddings**
  
  ```
  dataSales["Text Embedding"] = dataSales["Item Id"].apply(lambda x: glove.getMeanEmbedding(x))
  ```

- **# In this example we are using a 50d glove vector embedding**
  
  ```
  placeholders['embedding_dimension'] = ng.make_axis(length=50, name="F")
  placeholders['text_embedding'] = ng.placeholder(axes=[placeholders['embedding_dimension'],placeholders['N']], name="X_d")
  ```
Text data – ingestion

• # Embeddings data
glove = pd.read_csv('glove.6B.50d.txt', sep=" ", index_col = 0, header= None, quoting=csv.QUOTE_NONE)
• # Retrieving Embedding and missing data.
• def vec(w, glove):
    if w in glove.index:
        return glove.loc[w].as_matrix().T
    else:
        return np.ones(50)
def getAvrGlove(shortDesc):
    ns = shortDesc.values[0].split(" ")
a = np.empty(shape=[len(ns),50])
i=0
for w in ns:
    wl = w.lower()
    vecr = vec(wl)
a[i] = vecr
    i+=1
a=np.mean(a, axis=0)
return a
image data – bottleneck features

• # Getting the bottleneck features for the entire dataset.
• base_model = InceptionV3(weights='imagenet', include_top=False, pooling='max')

bfdict = {}
if product1 in filesIds:
    filename="images/" + filesIds[product1]
    bf = getBottleNeckFeatures( filename, base_model)
    bfdict[product1] = bf

# Save
np.save('bottleneckFeatures.npy', bfdict)
def getBottleNeckFeatures(product, image, model):
    bf = []
    if image is not None:
        img = Image.open(image)
        bf = bfeatures(model, img, target_size)
        bf = bf.flatten()
    return bf
image data – computing the features

- # Computing the bottleneck features
- target_size = (299, 299)
- def bfeatures(model, img, target_size):
  if img.size != target_size:
    img = img.resize(target_size)
  
  x = image.img_to_array(img)
  x = np.expand_dims(x, axis=0)
  x = preprocess_input(x)

  bf = model.predict(x)
  return bf
Evaluation Metric

The customer was interested in recommending the top 1 or 3 items of each customer. The metric chosen were top@3 and top@1 also known as precision at k.

Other metrics of interest if you want to used a rank web based perspective on the results:
- CG : Cumulative Gain
- DCG : Discounted Cumulative Gain
- NDCG : Normalized Discounted Cumulative Gain
results

Number of customers : 50K
Number of Items : 3K
Number of transactions : 250K
Call to action

• Try Deep Learning in your dataset or public available data.
• Check and Try the WD demo example in nGraph Library ® demos.
• Movielens a classical dataset to experiment.
• Netflix Prize Data another classic dataset.

https://grouplens.org/datasets/movielens/
https://www.kaggle.com/netflix-inc/netflix-prize-data
questions

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