AI DEVCON 2018

Deep Learning in Personalization: Developing a retail customer use case

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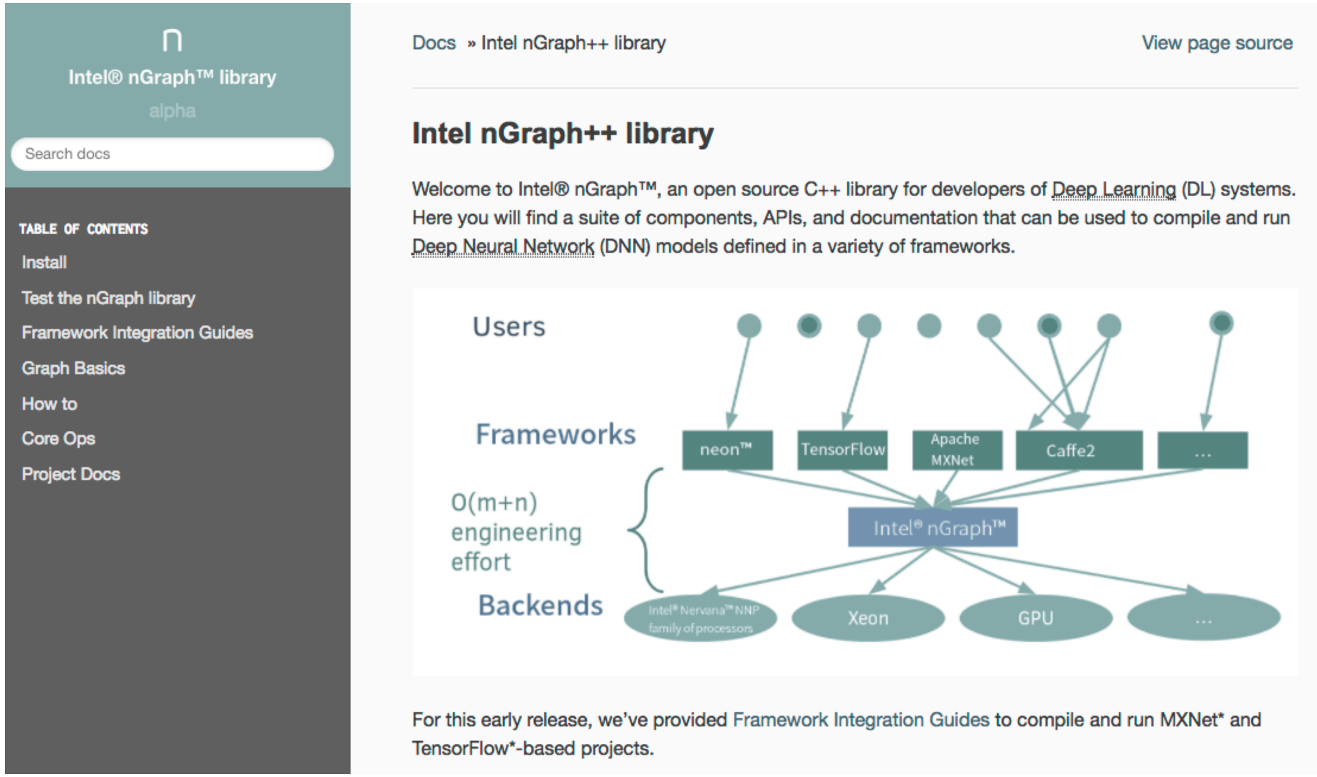
agenda

- 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


Intel® nGraph™ library

alpha

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Intel nGraph++ library

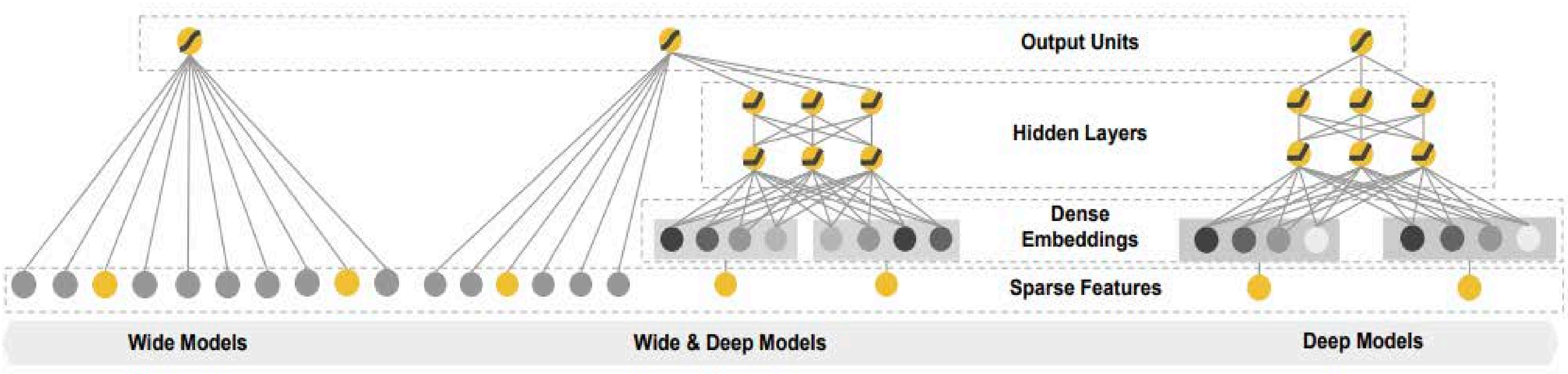
Welcome to Intel® nGraph™, an open source C++ library for developers of Deep Learning (DL) systems. Here you will find a suite of components, APIs, and documentation that can be used to compile and run Deep Neural Network (DNN) models defined in a variety of frameworks.

For this early release, we've provided Framework Integration Guides to compile and run MXNet* and TensorFlow*-based projects.

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_deep
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.

Data : pandas / SKlearn

- **#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():

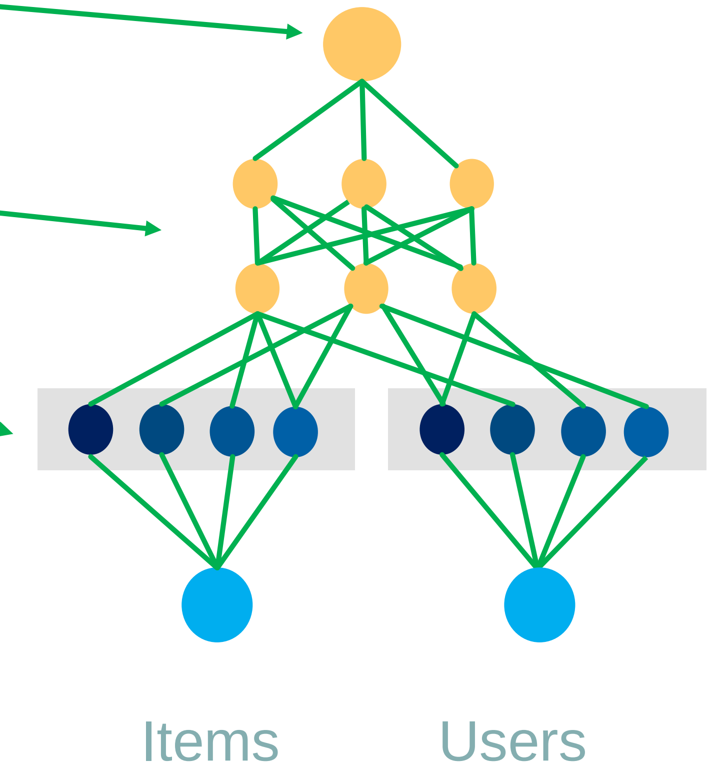
    if row[UID] not in customerDict.keys():
        customerDict[UID]=nCustomers
        nCustomers+=1
    if row[ItemID] not in itemDict.keys():
        itemDict[row[ItemID]] = nItems
        nItems +=1
```

- **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



MODEL – I/o

- **# Placeholders for the embeddings and the outputs**
- **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]

```
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)

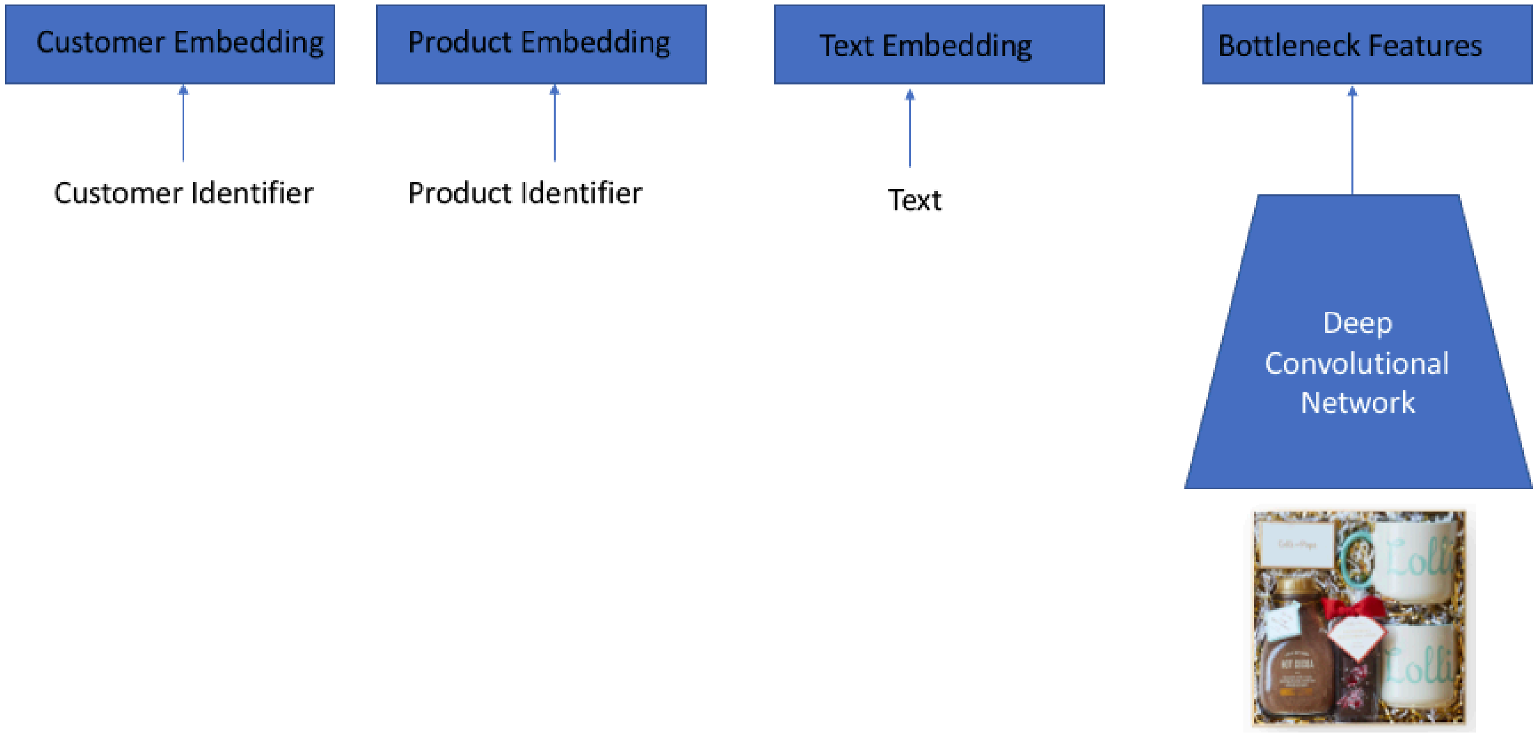
X_deep = ng.concat_along_axis(embedding_ops,ng.make_axis(name="F"))

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



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)
```

image data – process an image

- # Get the bottleneck features for a given image.

```
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):

```
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.

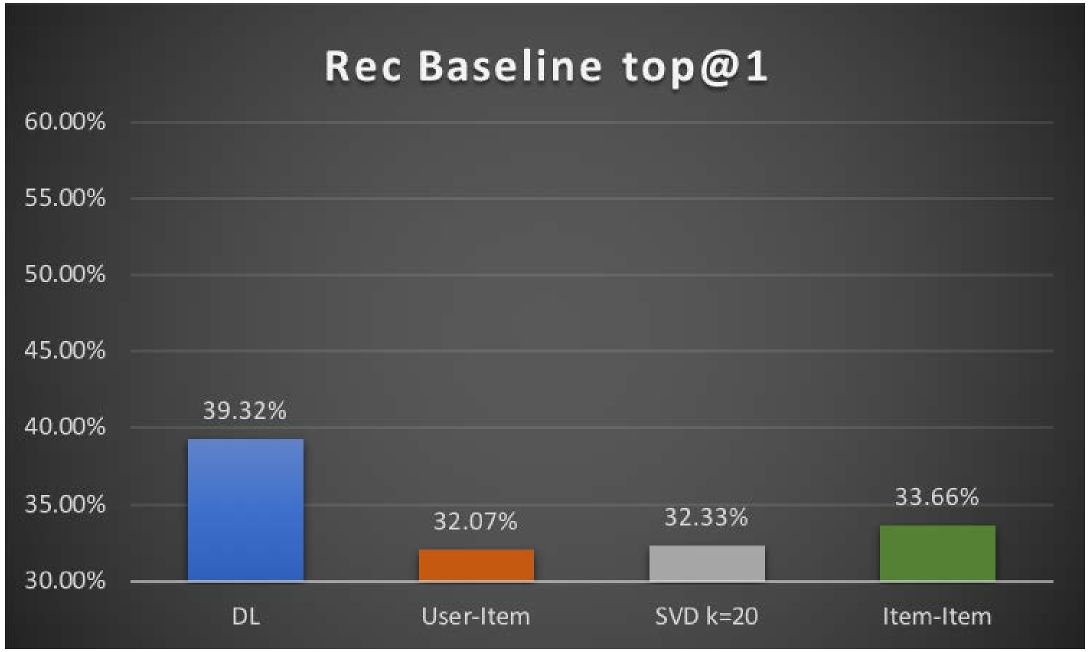
Other metrics of interest if you want to used a rank web based perspective on the results:

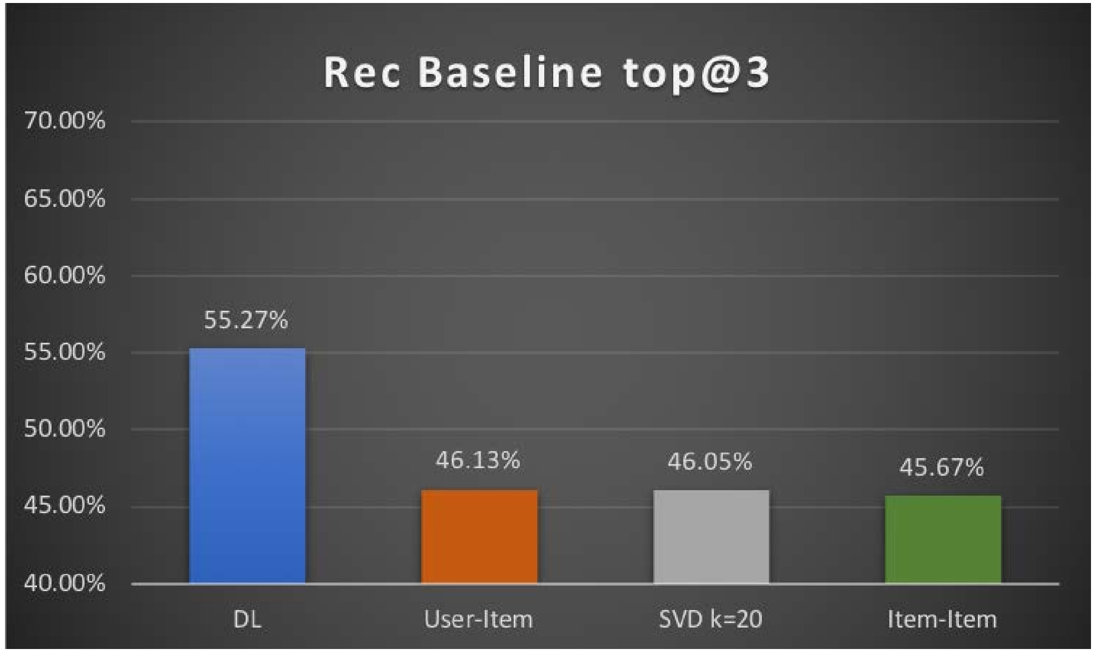
CG   : Cumulative Gain

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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