Smart Personalized Information Retrieval Environment

Presented by
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Enhancing Enterprise Search

SearchPoint Application Profile
- Deployed on Apache Solr search engine
- Migrating to LucidWorks Fusion
- 360,000 pages indexed
- Average of 13000 queries per day
- 8300 distinct customers submitted queries during the year

Recent Enhancements
- Applications that Listen
- Link popularity boosting
Exploring analytics to improve search results

- Click popularity boosting – Aggregate Behavior Model
- Word2Vec for synonym expansion
- Doc2Vec feature extraction for Related SAND reports
- General Reranker is a framework for evaluating these models
Presenting personalized recommendations

Multiple components already provide ranking inputs
- Core search engine uses term frequency based ranking (TF/IDF algorithm)
- Rankings adjusted by URL popularity boosting

Worked with the UX team to determine best display options

Decided to display recommendations in a separate panel
- Didn’t want another system competing to adjust rankings
- SPIRE recommendations are more course grained
- Want to distinguish them from pure content recommendations
- SPIRE Recommendations apply to customer not search term
- Verify that results contain at least one SAND from topic of interest
Pushing recommendations to the customer

- Email notifications are the push side of recommendations
- Need to prevent repeating previous recommendations
- Identify optimal frequency and provide opt-out capability
Providing personalized content recommendations

- SPIRE – Sandia Personalized Information Retrieval Environment
- Match customers with relevant content based on their information activities
- Group MOWs by their common interests
- Cluster related content by common term usage
- Develop predictive models that show who is likely to want which content
Profiling MOWs by activity

Customers are clustered based on their attributes and information usage
- Personal attributes: education, years at Sandia…
- Documents created: SAND reports, LDRDs, patents, PMF objectives …
- K-means used to cluster MOWs with K=30
Build SAND Report Classifiers

1. Classify documents into proper classes
2. Recognize the document class in various formats
3. Recognize the distribution of possible classes in a document

New SAND

New document

Trained Classifiers

Sensing 55%

Chemistry 15%

Simulating 30%

Distribution of Topics in a Document
Procedures

- Collected ~100,000 SAND reports over last 50 years
- Data cleaned and indexed with Apache/Lucene
- Built “Taxonomy” for Sandia Category Guide (SCG)
- Selected the highly ranked documents with SCG taxonomy terms/phrases as the training sets
- Build a Word2Vec language model for embedding representatives of words
- Built a Convolutional Neural Network (CNN)
- Trained the network with various hyperparameters
Build “Taxonomy” based on Sandia Category Guide (SCG)

Category (Material Sciences)
   Subcategories:
      Ceramics
      plastics
      seals and Adhesives

Obtain the terms/phrases for subcategories from:
   Documents created by Sandia authors
   Wikipedia
   Word2Vec built on Sandia’s documents
   Internal Organization webpages

Taxonomy Example for “Material Sciences/Composite Materials:
   “carbon composite” “carbon fiber” “ceramal” “ceramic composite”
   “ceramic matrix composite” “CFRP” “Chobham armour” “clad metals” “CMC”
   “composite material” “concrete-plastic composite” “fiber reinforced composite”
   “fiber reinforced polymer” “fiberglass” “formica” “FRP” “glasdpolyester”
   “graphite” “GRP” “lamine” “Mallite” “metal composite” “metal matrix composite”...

NOTE: Taxonomy used here is simplified from Jessica Shaffer-Gant’s version
Collect Sets of Labeled Documents for Training

Terms/Phrases from Taxonomy

Labeled and Ranked Documents

Ceramics
Sensing
Geosciences
Solid Physics
print('Training model.

# train a 1D convnet with global maxpooling
sequence_input = Input(shape=(MAX_SEQUENCE_LENGTH,),
dtype='int32')
embedded_sequences = embedding_layer(sequence_input)
x = Conv1D(128, 5, activation='relu')(embedded_sequences)
x = MaxPooling1D(5)(x)
x = Dropout(0.5)(x)
x = Conv1D(128, 5, activation='relu')(x)
x = Dropout(0.5)(x)
x = MaxPooling1D(5)(x)
x = Conv1D(128, 5, activation='relu')(x)
x = Dropout(0.5)(x)
x = MaxPooling1D(35)(x)
x = Flatten()(x)
x = Dense(128, activation='relu')(x)
preds = Dense(len(labels_index), activation='softmax')(x)
model = Model(sequence_input, preds)
model.compile(loss='categorical_crossentropy', optimizer='rmsprop',
metrics=['acc'])

Modified from a Keras example
prediction = model.predict(data[146:150])

[37 1] [ 6.892 79.014] % SAND2000-0217.txt thermodynamics atmospheric sciences
[16 31] [ 6.668 60.088] % SAND2000-0221.txt fluid mechanics plasma physics
[29 29] [ 29.797 52.055] % SAND2000-0222C.txt computer architecture optics

<table>
<thead>
<tr>
<th>Class ID</th>
<th>Class Distribution</th>
<th>SAND ID</th>
<th>Class Names</th>
</tr>
</thead>
</table>
Example of Classifying a Document

[37 1] [6.892 79.014] % SAND2000-0217.txt thermodynamics atmospheric sciences
Building a Graphic Model for Prediction

\[ P(E \mid \mathcal{O} \ F) = \frac{E \ F \ (\mathcal{O} \mid \mathcal{E})}{(\mathcal{E})} \]

- **Posterior probability of ‘x’ given the evidence ‘E’**
- **Prior probability**
- **Likelihood of the evidence of ‘E’**
  - If the hypothesis ‘x’ is true
- **Prior probability that the evidence itself is true**
If one is a smoker, what is the probability he/she may have lung cancer?

\[ P_{\text{E L CöSF}} = \frac{0.00006 * 0.7}{0.2} = 0.00021 \]

Probability of Lung cancer patients among people

Probability of smokers among lung cancer patients

\[ 0.00021 = 3.5 = 350\% \]
Building a Graphic Model for Prediction

\[ P \text{E} \bigotimes \text{F} = \frac{E \text{F} \times \left( \frac{\text{webDev} \mid \text{computer}}{\text{computer}} \right)}{\text{P(webDev)}} \]
Distribution of Sandia R&D S&E Clusters and Usage of SAND Reports
Comparison of SAND Reports Checked by Nuclear-Waste Management and Other Groups

Geoscience 1.86% to 22.14%
Nuclear science 6.32% to 14.04%
Fluid mechanics 5.71% to 14.18%
Comparison of SAND Reports Checked by Machine-learning and Other Groups

- Computer intelligence: 3.82% to 14.18%
- Mathematics: 3.09% to 7.47%
- Modeling simulation: 4.19% to 7.77%
How personalized recommendations are determined

The User

Sand classes interested

Queried SAND

Recommended SANDS
How personalized recommendations are determined

The User

Sand classes interested

Queried SAND

Recommended SANDS

Interested Sand Classes for User: jherzer are:
Computational_Intelligent
Computer_theory_and_algorithms
Networking

Number of SAND Reports: 32
Enter a username, or 'q' to quit
> jherzer
Jherzer
27
Masters
Marginal probability tables:
woo

[Code snippet showing recommendation process]
Quantum computing is and is not amazing
SAND2017-7067C

Searched SAND Report by jherzer

Heuristic approach to Satellite Range Scheduling with Bounds using Lagrangian Relaxation
SAND2017-2553J

Quantum Approximation Algorithms
SAND2017-7463C

Approximate Constraint Satisfaction in the Quantum Setting
SAND2017-9140C

The Trilinos Project Exascale Roadmap
. Contributors: Mark Hoemmen, Siva Rajamanickam, Tobias Wiesner, Lois McInnes trilinos.github.io SAND2017-8287PE

A Hierarchical Low-rank Solver for Sparse Linear Systems
SAND2017-2694C

Recommend to jherzer the SANDs related to his search by SPIRE
Achievements and Further Efforts

- Analytics provide the foundation to build up an intelligent information retrieval environment:
  - Understanding the similarities of employees through clustering
  - Collecting labeled documents for Machine Learning guided by Taxonomy
  - Classifying text documents with trained classifiers

- Probabilistic graphic model associates users and documents:
  - The model reasons and infers information needed by users
  - The model will be used to predict users’ information needs

- More work needed to build a better taxonomy to select labeled documents for learning
  - This is always the issue for supervised learnings

- Expanding the Personalized Information Pull and Push mechanisms to cover more MOWs and other document types. Ideally, to all employees and to all data repositories
Questions