# Calculate Cosine Similarity Score

- Input
  - Query
  - Posting List
- Output
  - List of 10 top ranked documents

# Calculate Cosine Similarity Score

- Remember what this is about
  - A query as a vector
  - A corpus as a term-document matrix
    - Where each document is a column in the matrix

$$sim(q,d) = \frac{\vec{V}(q) \cdot \vec{V}(d)}{|\vec{V}(q)||\vec{V}(d)|}$$

# Calculate Cosine Similarity Score

- We are not going to calculate the similarity score of a query with every document
  - That would be inefficient.
  - Many scores are zero.
- We are not going to actually create a term-document matrix
  - The posting list has all the information that we need to calculate the similarity scores

# Calculate Cosine Similarity Score

- We are going to calculate the cosine similarity score, but in a clever way.
- Here are some constants we will need:
  - The number of documents in the posting list (aka corpus).
    - Figure this out when creating the corpus (new thing)
  - The document frequency of a term
    - This should be the number of items in a row of the posting list.  (each term has its own row)
  - The term frequency of a term in a document.
    - Different for every term document pair.

# Calculate Cosine Similarity Score

- Steps
  - Get a query from the user
  - Convert it to TF-IDF scores

$$tfidf(t,q) \quad = \quad WTF(t,q) * log\left(\frac{|corpus|}{df_{t,q}}\right)$$

$\mathrm{WTF}(t,q)$
1 **if** $tf_{t,q} = 0$
2 **then** $return(0)$
3 **else** $return(1 + log(tf_{t,q}))$

# Calculate Cosine Similarity Score

- "UCI Informatics Professors"
  - 3 terms {"UCI", "Informatics", "Professors"}
  - 3 TF-IDF scores
    - Size of the corpus comes from the posting list
    - The document frequency of "UCI" comes from the number of entries in the posting list for "UCI"
      - use 1 if your posting list is too small
  - The term frequency is 1/3

$$tfidf(\text{“}UCI\text{”}, \text{“}UCI\ Informatics\ Professors\text{”}) \quad = \quad 1 + log(1) * log\left(\frac{|corpus|}{(df_{\text{“}UCI\text{”}} + 1)}\right)$$

# Calculate Cosine Similarity Score

- Steps
  - Get a query from the user
  - Convert it to TF-IDF scores
  - Create a data structure that is indexed by documents
    - Which will accumulate scores for the documents
    - so like, Scores = new Hashmap<String,Double>()

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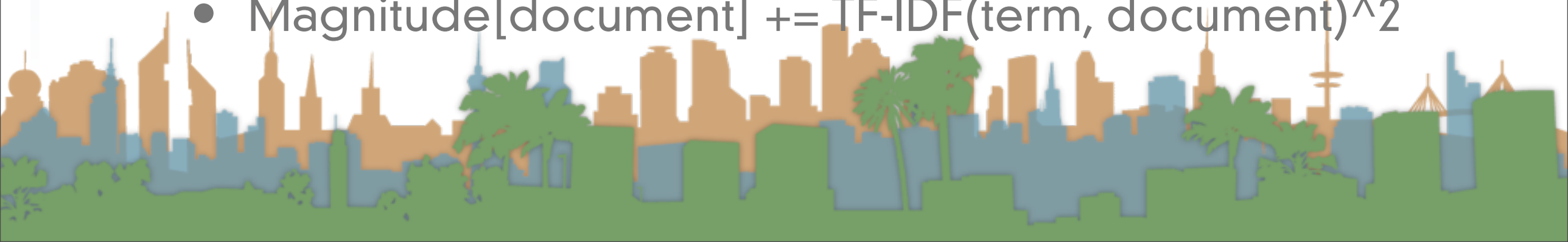
- For each term in the query
  - Get the posting list for the term
  - For each document that has that term we are going to update the entry in Scores

# Calculate Cosine Similarity Score

- Steps
  - For each term in the query
    - Get the posting list for the term
    - For each document that has that term we are going to update the entry in Scores
- Scores[d] += TF-IDF(term,query) * TF-IDF(term, document)

# Calculate Cosine Similarity Score

- At the end of this we will have the data structure Scores
- Which for “UCI Informatics Professors” required looking up 3 posting lists
- Finally the scores must be normalized so we can compare them against each other.
- Create a new data-structure like Scores called Magnitude
- For each term in the entire posting list
  - For each document represented in Scores
    - Magnitude[document] += TF-IDF(term, document)^2



# Calculate Cosine Similarity Score

- Now we have Scores and Magnitude
- Now we calculate the highest rankings
- For each document in Scores
  - Double x = Scores[document]/sqrt(Magnitude[document])

# Calculate Cosine Similarity Score

- Summary
  - Get query from user, transform to TF-IDF
  - Pull out a few postings to calculate scores
  - Look at every positing to calculate magnitudes
  - Calculate final scores
  - Output URLs and scores of highest documents

# Calculate Cosine Similarity Score

```
CosineScore(q)
 1  Initialize(Scores[d ∈ D])
 2  Initialize(Magnitude[d ∈ D])
 3  for each term(t ∈ q)
 4      do p ← FetchPostingsList(t)
 5          df_t ← GetCorpusWideStats(p)
 6          α_{t,q} ← WeightInQuery(t, q, df_t)
 7          for each {d, tf_{t,d}} ∈ p
 8              do Scores[d] += α_{t,q} · WeightInDocument(t, q, df_t)
 9  for d ∈ Scores
10      do Normalize(Scores[d], Magnitude[d])
11  return top K ∈ Scores
```

# Evaluation in IR

## Introduction to Information Retrieval
## CS 221
## Donald J. Patterson

Content adapted from Hinrich Schütze
http://www.informationretrieval.org
~Sage~
http://www.flickr.com/photos/vickispix/2089649326/

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# Outline

- Intro to Evaluation
- Standard Test Collections
- Evaluation of Unranked Retrieval
- Evaluation of Ranked Retrieval
- Assessing relevance
- Broader perspectives
- Result Snippets

# Intro to Evaluation

- There are many implementation decisions to be made in an IR system
  - Crawler
    - Depth-first or breadth-first?
  - Indexer
    - Use zones?
    - Which zones?
    - Use stemming?
    - Use multi-word phrases? Which ones?

# Intro to Evaluation

- There are many implementation decisions to be made in an IR system
  - Query
    - Ranked Results?
    - PageRank?
  - Which formula do we use in the TF-IDF Matrix?
  - Should we use Latent Semantic Indexing?
    - How many dimensions should we reduce?

# Intro to Evaluation

- There are many implementation decisions to be made in an IR system
  - Results
    - How many do we show?
    - Do we show summaries?
    - Do we group them into categories?
    - Do we personalize the rankings?
    - Do we display graphically?

# Intro to Evaluation

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- How can we evaluate whether we made good decisions or not?

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- How can we evaluate whether we made good decisions or not?
  - Measure them

# Measures for a search engine

- How fast does it index?
  - Number of documents per hour
  - Average document size
- How fast does it search
  - Latency as a function of index size
- Expressiveness of query language
  - Ability to express complex information needs
  - Speed on complex queries

# Measures for a search engine

- We can measure all of these things:
  - We can quantify size and speed
  - We can make this precise
- What about user happiness?
  - What is this?
  - Speed of response/size of index are factors
  - But fast, useless answers won't make a user happy
- Need to quantify user happiness also.

# Measuring user happiness

- Issue: Who is the user we are trying to make happy?
  - It depends.

# Measuring stakeholder happiness

- Issue: Who is the user we are trying to make happy?
  - Web engine:
    - The user finds what they want.
    - Measure whether or not they come back.