How useful are results from simulated offline IR collections?

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Simulating Information Retrieval Test Collections

1. Why? — Motivations for simulation
2. How? — Simulation methods
3. How good is simulation?
4. Whether? — Risk-benefit discussion
5. Who? When? — History of simulation in IR
Why?

- Tuning, training, resource allocation on private collections
- Reproducible efficiency experimentation
  - Ability to engineer corpus properties
- Meaningful study of scalability
How?

- Language models, LDA topic models
- Markov
- Encryption - Caesar, Nomenclator
- Macro methods, e.g. Synthacorpus
- Neural methods: LSTMs, GPT-2

PANDARUS:
Alas, I think he shall be come approached and the day
When little strain would be attain’d into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,

https://bitbucket.org/davidhawking/synthacorpus
Corpus emulation with SynthaCorpus

Usage: emulateARealCorpus.pl <corpus_name> <tf_model> <doc_length_model> <term_repn_model> <dependence_model> [-dependencies=neither|both|base|mimic]

<corpus_name> is a name (e.g. TREC-AP) not a path. We expect to find a single file called <corpus_name>.tsv, <corpus_name>.trec, or <corpus_name>.starc in the directory ../Experiments/Base

<tf_model> ::= Piecewise|Linear|Copy
If Piecewise we'll use a 3-segment term-frequency model with 10 headpoints, 10 linear segments in the middle and an explicit count of singletons. If Linear we'll approximate the whole thing as pure Zipf. If Copy we'll copy the exact term frequency distribution from the base corpus.

<doc_length_model> ::= dlnormal|dlsegs|dlhisto
If dlhisto or dlsegs is given, the necessary data will be taken from the base corpus. Recommended: dlhisto (Unfortunately dlgamma not available in this version)

<term_repn_model> ::= tnum|base26|bubble_babble|simpleWords|from_tsv|markov-9e?
The Markov order is specified by the single digit, represented by '9'. If present, the 'e' specifies use of the end-of-word symbol. Otherwise a random length will be generated for each word and it will be cut off there. The Markov model will be trained on the base corpus. If from_tsv is given, the vocab will be that of the base corpus. Recommended: from_tsv if appropriate or markov-5e (6e or 7e on large RAM machines)

<dependence_model> ::= ind|ngrams[2-5]|bursts|coocs|fullddep
Currently, only ind(ependent) and ngramsX are implemented. Ind means that words are generated completely independently of each other. Fullddep means ngrams + bursts + coocs. Dependence models are only applied if the relevant files, i.e ngrams.termids, bursts.termids, coocs.termids, are available for the base corpus.
How good is an emulation?

Real Corpus → Real Performance Measure $R$ → IR System (identical) → Emulated Performance Measure $E$ → Emulation Method → Emulated Corpus

Prediction Accuracy = $\frac{\min R, E}{\max R, E}$
Using simplified Azzopardi, de Rijke, Balog method for generating known item queries:

• Each query set contains 1000 queries
Let’s compare the prediction accuracy of 5 emulation methods across 8 underlying measures, 4 base corpora, and 3 retrieval systems
Which corpora?

- TREC ap
- TREC fr
- TREC patents
- WT10g

After running base corpora through detrec to reduce to:
  - indexable words, plus
  - document boundary markup: DOC and DOCNO,
  - after converting character encodings to UTF-8.

(Emulation methods produce the same format.)
Which retrieval systems?

- Indri (LM)
- Terrier (DFR)
- ATIRE (BM25)
Which emulation methods?
Real
<DOC>
<DOCNO> AP880212-0001 </DOCNO>
<TEXT>
Reports Former Saigon Officials Released from Re education
Camp More than 150 former officers of the overthrown South
Vietnamese government have been released from a re education
camp after 13 years of detention the official Vietnam News
Agency reported Saturday ...
</TEXT>
</DOC>

SophSynth
crash praisal pi in crash do kamleh ik crash nomadic vauhgan
gimbels crash oo ut boo crash de ux boo crash de ux nev crash
abu iba ma crash xa bogersonellaeg boo crash hob coatham fle

Caesar
Sfqsuts Gpsnfs Tbjhpo Pggjdbmt Sfmbtfe gspn Sf fevdbujpo Dbnq Npsf
uibo 261 gpsnfs pggdjfst pg uif pwfsuispxo Tpvui Wjfuobnftf hpwsonfou
ibiw cffo sfmbtfe gspn b sf fevdbujpo dbnq bgufs 24 zfbst pg
efoujpo uif pggjdbm Wjfuobn Ofxt Bhfodz sfqsutsfe Thuveszb Uif
sfqsut gspn Ibojy npojupsfe jo Cbohlpl eje opu hjwf tfqfdjgd gjhvsf

Nomenclator
moschorsholt biarrithem vladish esbuscovar ngau competanya padrnos
kumsisant fu derauding abori cristyn bederick vladish chalis gierkeg
herbed bullistoforceab caspermentativ esthetelyal nhilunby carlatt
bonnoticeable competanya padrnos aci kumsisant fu derauding juicines
recurragchaa scaffold gierkeg guntumble herbed destructuring sepeate
• /bin/cp — indication of noise
• Caesar substitution
• Nomenclator substitution
• SynthaCorpus Sophisticated
• SynthaCorpus Simple

<table>
<thead>
<tr>
<th>Emulation method</th>
<th>Preservation of confidentiality</th>
<th>Expected prediction accuracy rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Copy</td>
<td>None</td>
<td>1</td>
</tr>
<tr>
<td>Caesar</td>
<td>None</td>
<td>2</td>
</tr>
<tr>
<td>Nomenclator</td>
<td>OK in limited circumstances.</td>
<td>3</td>
</tr>
<tr>
<td>SophSynth</td>
<td>Good</td>
<td>4</td>
</tr>
<tr>
<td>SimpleSynth</td>
<td>Good</td>
<td>5</td>
</tr>
</tbody>
</table>

We emulated TREC-AP with a neural method GPT-2 — too slow to include in this experiment.
Which underlying measures?

- Indexing time
- Indexing memory use
- Query processing (QP) time (3wd, 6wd, 9wd query sets)
- Mean reciprocal rank (3wd, 6wd, 9wd query sets)
Accuracy scores averaged across all the measures, all the retrieval systems, all the query lengths, and all the corpora.

- Solid — 2nd and 3rd quartiles
- Whisker — range
- Green — mean

Each data point is the mean of five trials. A new query set is generated for each trial.

Cp noise due to disk layouts and variation in query sets.

Left to right decline is as expected.

A lot of variation, even for the best emulation methods.
Accuracy scores for **Indexing Time** averaged across all the retrieval systems and all the corpora.

Less noise for Cp because no variance due to query generation.

SimpleSynth is much worse, presumably because word frequency distribution is uniform.
ATIRE clearly reported memory use. I couldn’t see how to obtain meaningful figures for the others.

Interesting that SimpleS is so different. $|V|$ and N are the same as for other methods, word freq. list. and term representations are very different.
Very wide variation in prediction accuracy for time to process 1000 queries. None of the emulation methods give reliable predictions.

Like to make a hypothesis?

Accuracy scores for *Query Processing Time* averaged across all the query lengths, all the retrieval systems and all the corpora.
Four emulation methods give very good prediction of MRR performance.

With a uniform word freq. distribution, SimpleSynth makes it difficult to choose queries which discriminate a known item.
Accuracy scores per retrieval system averaged across all the query lengths, all the measures and all the corpora

Nomenclator gives worse predictions for ATIRE than for the other two.

SophSynth gives worse predictions for Indri than for the other two.
Accuracy scores per corpus averaged across all the query lengths, all the retrieval systems and all the measures

Clearly there is something of a corpus effect — see WT10g.SimpleSynth.

I have decided not to show you accuracy results for the 5 x 4 x 4 = 80 individual conditions 😊
Whether?
• Cp and Caesar are just baselines — can’t be used in a confidentiality environment.

• Opinion: SimpleSynth doesn’t make good enough predictions.

• Opinion: Only Nomenclator and SophSynth make accurate enough predictions for use in practice.

• Opinion: It would be hard to crack rare words in Nomenclator, even through n-gram frequency attack, or with the availability of some plain-cypher paired text.

• Opinion: SynthaCorpus methods do not leak confidential information.

• Data Owner’s Opinion: Whether Nomenclator or SynthaCorpus methods provide sufficient protection.
• SynthaCorpus provides a compact means (parameters + random seed) by which a researcher can allow reproduction of experimental results obtained on a private corpus.

• SynthaCorpus can engineer corpora with specific properties to explore and understand the behaviour of IR systems.

• SynthaCorpus incorporates growth models which allow realistic scaling up of a corpus, including vocabulary growth (à la Herdan / Heaps), thus permitting meaningful study of algorithmic scalability
Who?  When?
• 1966 C.R. Blunt et al — simulating information storage and retrieval systems.

• 1973 M.D. Cooper — artificial corpora (tiny!) built from topic models

• 1980 J. Tague et al — simulation of document term matrix

• 1996 T. Kanungo — generation of degraded text

• 2000 E. Reiter et al — Building natural language generation systems

• 2006/7 L. Azzopardi — building simulated queries

• 2010 D.L. Chen et al — automated sportscasting

• 2011 I. Sutskever et al — generating text with recurrent neural networks. Also Karpathy, Radford et al.

• 2012/13 R. Berendsen et al — generating test collections for learning to rank

• 2016 D. Maxwell et al — simulated users

Please let me know of any other relevant work 😊
Nomenclator explanation

Plain Text: Around the rugged rocks the ragged rascal ran.

Relevant part of nomenclator table:
- around → Smith
- ragged → twice
- ran → and
- rascal → Tuesday
- rocks → B52
- rugged → it
- the → furlong

Ciphertext: Smith furlong it B52 furlong twice Tuesday and