IR From Bag-of-words to BERT and Beyond through Practical Experiments

A Search Solutions 2022 tutorial with PyTerrier

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*(*Alphabetical ordering)*

Tutorial Schedule

10:00-11:30	Part 1 Presentation (a): Indexing, Retrieval, Evaluation
11:00-11:15	Morning break
11:15-11:45	Part 1 Presentation (b): Learning-to-rank
11:45-12:15	Part 1 Lab
12:15-13:00	Lunch break
13:00-14:00	Part 2 Presentation: Neural re-ranking
14:00-14:30	Part 2 Lab
14:30-14:45	Afternoon break
14:45-15:45	Part 3 Presentation: Learned sparse, Dense retrieval
15:45-16:15	Part 3 Lab


IR is Experiencing a Renaissance!
Neural Models
Lexical Models
Src: http://wallpapers4screen.com/download/original/21736

This provides the 2 primary goals of this tutorial

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Deep neural network models

Particularly contextual language models, which have allowed whole new areas of research to open up.

***Review** recent advances in neural text rankers & **experience** them in PyTerrier*

This drives us to ensure that we have the correct tools (IR *platforms*) for the next generation

***Experience** a new way of doing IR experiments using PyTerrier*

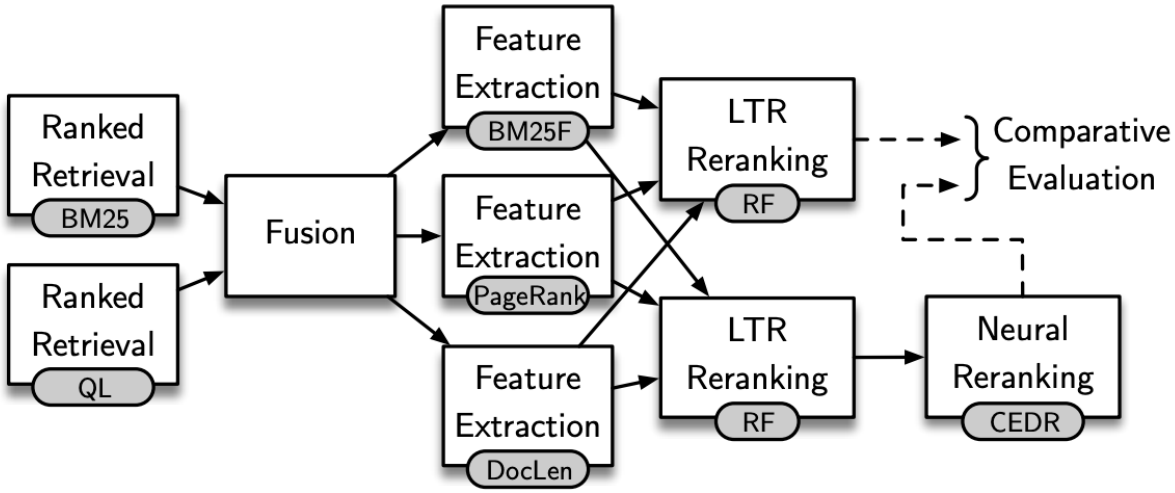
But why is it that we need new tools for IR? Any why in Python?

So what is required for modern IR platforms

Python!

- Easy to write, and easy to integrate with NN frameworks

Moving beyond imperative *"for each query, for each document"* programming – we need an expressive language for constructing complex IR retrieval pipelines



Towards Declarative Information Retrieval

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We need a (Python) language for describing what our IR pipeline will do (not how)

- Linear combinations, re-rankers (incl. neural)
- This moves IR towards a declarative manner of writing code

Many IR tools still use `trec_eval` for evaluation – an inherently file-based workflow

- We show an alternative declarative workflow in PyTerrier, based on operations upon Python (Pandas) dataframes (relations)

Indeed, all common IR operations can be expressed within the PyTerrier workflow

Outline

1000-1100	**Part 1(a) – *Classical* IR: Indexing, Retrieval & Evaluation**
	– *Modern* Retrieval Architectures: PyTerrier data model and operators
1115-1145	**Part 1(b) Exemplar using learning-to-rank**
1145-1215	**Part 1 Lab**
1300-1400	**Part 2 – *Contemporary* Retrieval Architectures: Neural re-rankers: BERT, monoT5, ColBERT**
1400-1430	**Part 2 Lab**
1445-1545	**Part 3 – *Recent* Advances beyond the classical inverted index: doc2query, dense retrieval**
1545-1615	**Part 3 Lab**

Review & Experience

Principles

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We **review** *classical*, *modern*, *contemporary* and *recent* techniques

You **experience** these techniques within PyTerrier

In each part of the tutorial, we reserve 30 minutes for hands-on practical work

We provide Google Colab notebooks with examples based on the **TREC CORD19** (Covid) test collection

Live tutoring help

Links

PyTerrier repository

- https://github.com/terrier-org/pyterrier

PyTerrier documentation

- https://pyterrier.readthedocs.io

Tutorial repository

- Notebooks
- Slides
- https://github.com/terrier-org/searchsolutions2022-tutorial

Your Presenters Today

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Intended Learning Outcomes (1/4)

Part 1 – *Classical* IR: Indexing, Retrieval and Evaluation

ILO 1A. Describe classical retrieval architecture components based on bag-of-words, including inverted index data structures and ranked retrieval.

ILO 1B. Manipulate index document collections, perform retrieval from indices, and access classical inverted index data structures within a Python notebook.

ILO 1C. Evaluate two retrieval systems using PyTerrier

Intended Learning Outcomes (2/4)

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Part 1 (cont.) – *Modern* Retrieval Architectures: PyTerrier data model and operators, towards re-rankers and learning-to-rank

ILO 1D. Understand modern retrieval architectures, such as re-rankers and ranking pipelines incorporating learning-to-rank strategies.

ILO 1E. Understand how different ranking and re-ranking operations can be *composed* to make more complex ranking models, in a declarative manner and leveraging a specific data model.

ILO 1F. Perform retrieval experiments within a Python notebook, including use of different features and learning-to-rank

Intended Learning Outcomes (3/4)

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Part 2 – *Contemporary* Retrieval Architectures: Neural re-rankers such as BERT, monoT5, ColBERT

ILO 2A. Understand contemporary retrieval architectures, such as using BERT, EPIC, ColBERT, and T5 as neural re-rankers.

ILO 2B. Understand how query time latency can be reduced by pre-computing representations or using neural models to augment an inverted index.

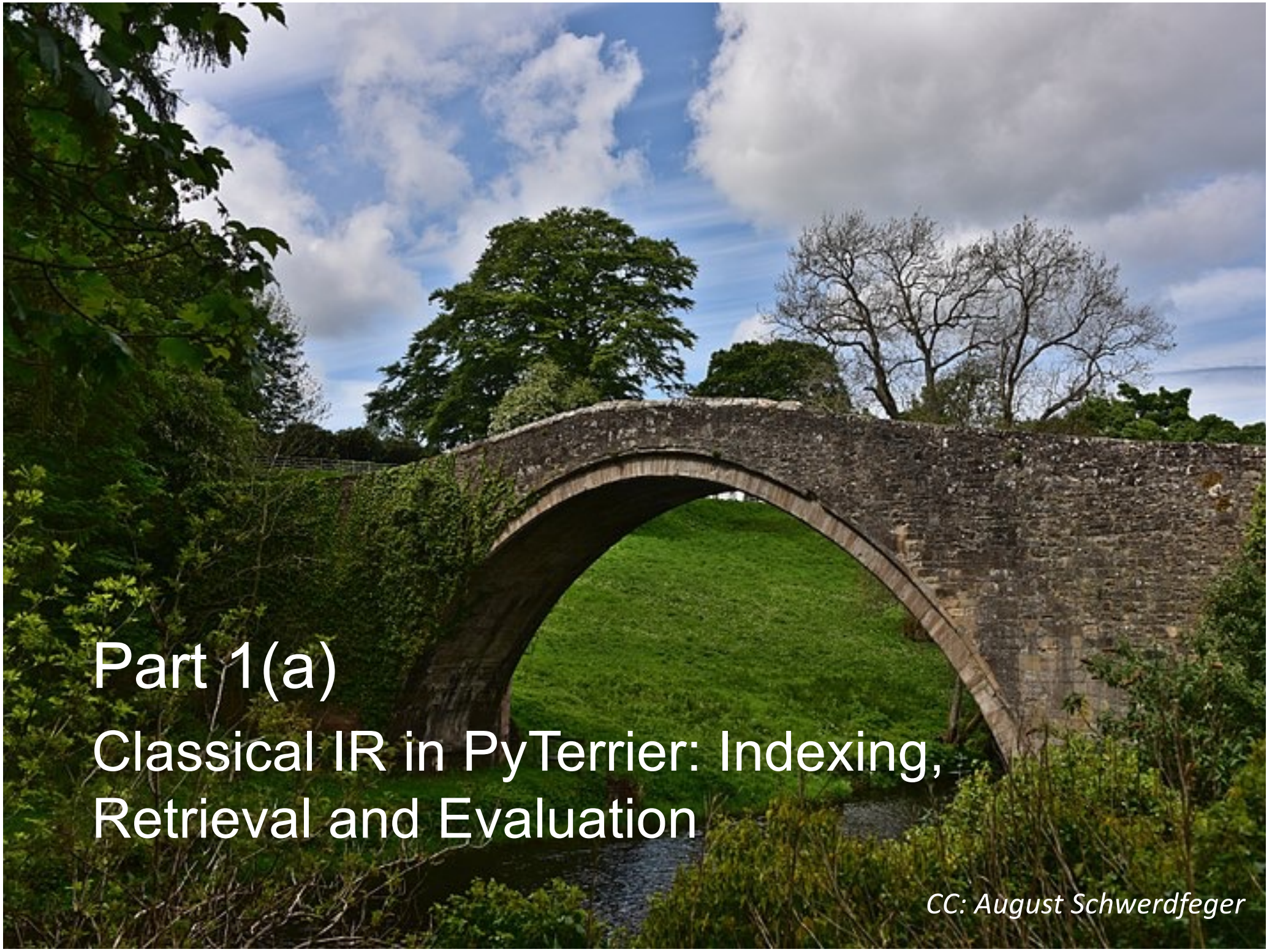
ILO 2C. Perform experiments with BERT, EPIC, T5, DeepCT, and doc2query in a Python notebook.

Intended Learning Outcomes (4/4)

Part 3 – *Recent* Advances beyond the classical inverted index: learned sparse retrieval & dense retrieval

ILO 3A. Understand the most recent effective retrieval architectures that learn representations of documents, both in leveraging traditional index structures (sparse retrieval), as well as new similarity search systems (dense retrieval)

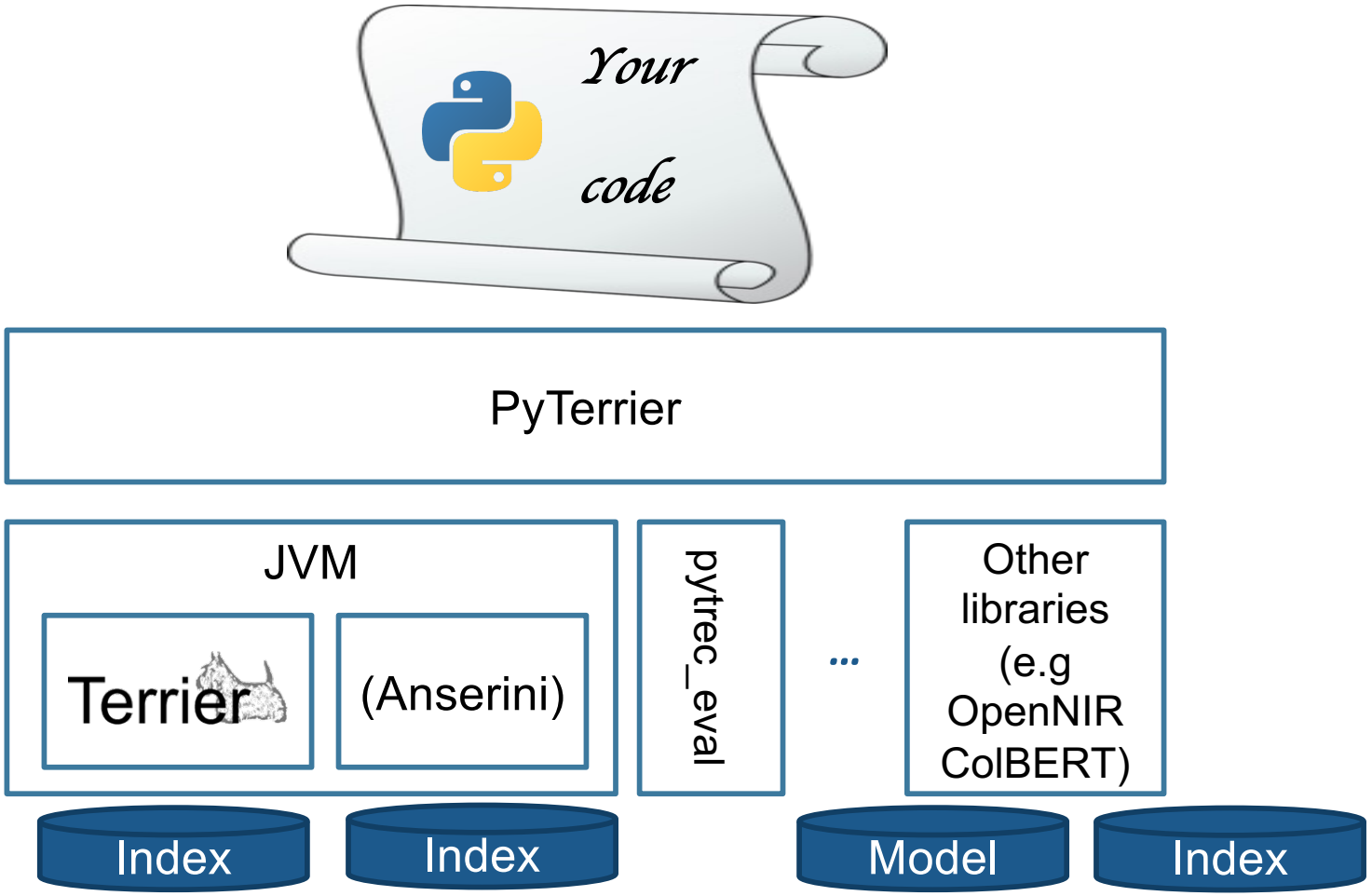
ILO 3B. Experience DeepImpact sparse retrieval approaches, as well as ANCE and ColBERT dense retrieval approaches


Part 1(a)
Classical IR in PyTerrier: Indexing, Retrieval and Evaluation
CC: August Schwerdfeger

What is PyTerrier

A Python layer above Terrier (and *other* IR platforms)

A Python framework for expressing and evaluating IR experiments



Goals and Anti-goals

Goals	Anti-goals
Work exclusively in Python	No extra configuration files
Minimal installation	No results files
Indexing of existing collections (e.g. from TREC)	Not just Terrier
Available standard retrieval techniques	Avoiding writing new Java code
Easy evaluation	Avoiding writing command-line scripts
Easy integration for learning-to-rank [part 1b]	
Easy integration for neural re-rankers [part 2]	

In Part 1

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"From bag-of-words"

Classical IR in PyTerrier: Indexing, Retrieval and Evaluation

1. Getting started
2. Indexing
3. Retrieval
4. Evaluation

Lets get started…

Install PyTerrier

```
pip install python-terrier
```

We do semi-regular releases

Get things going:

```
import pyterrier as pt
pt.init()
```

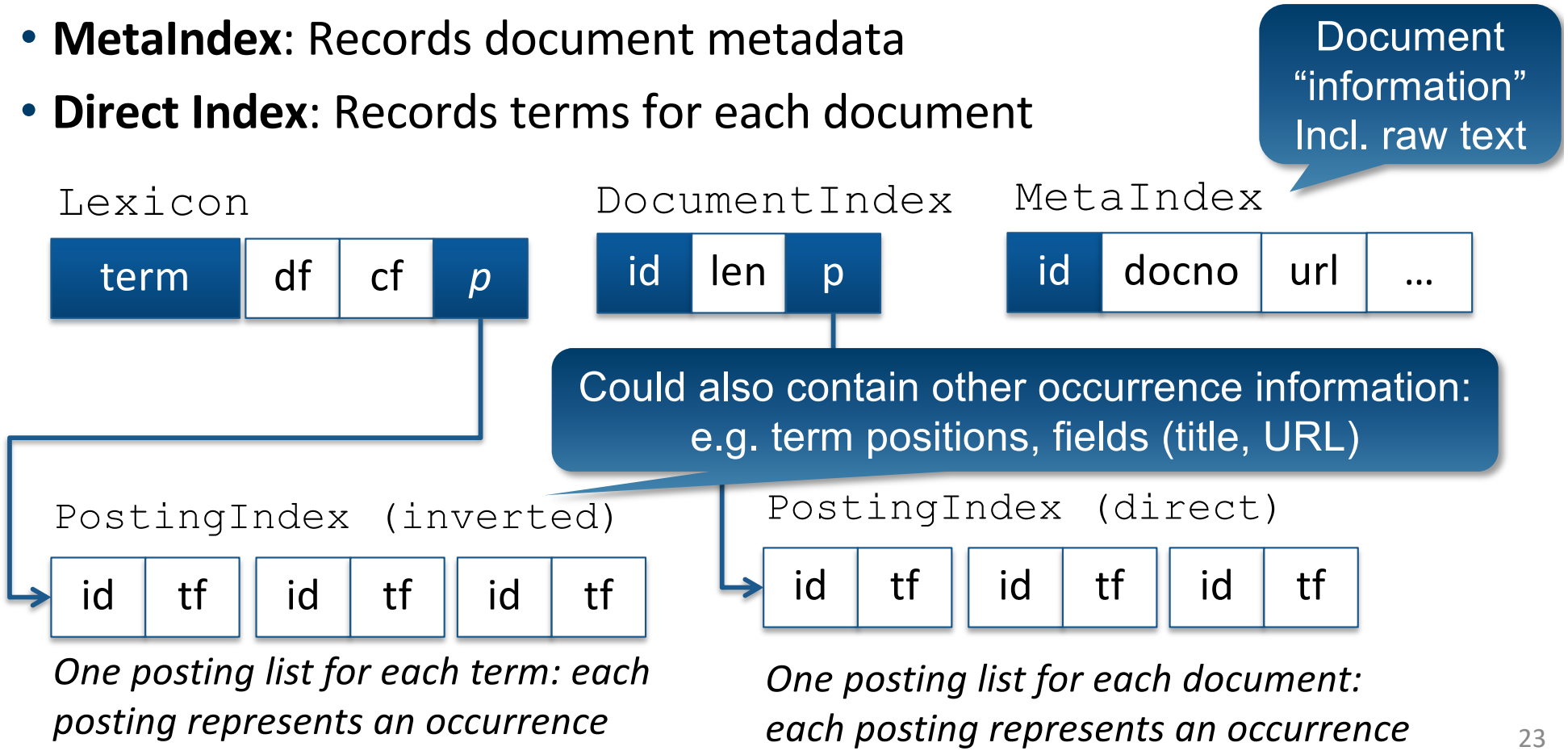
```
terrier-assemblies 5.4  jar-with-dependencies not found, downloading to /root/.pyterrier...
Done
terrier-python-helper 0.0.5  jar not found, downloading to /root/.pyterrier...
Done
PyTerrier 0.4.0 has loaded Terrier 5.4 (built by craigm on 2021-01-16 14:17)
```

JAR files for Terrier etc are downloaded automatically

The Format of a ("Sparse") Index

An index normally contains several data structures

- **Lexicon**: Records the list of all unique terms and their statistics
- **Document Index**: Records the statistics of all documents
- **Inverted Index**: Records the mapping between terms and documents. Contains many posting *lists*.
- **MetaIndex**: Records document metadata
- **Direct Index**: Records terms for each document



Creating an Index

Lets consider a few sample documents

```
df = pd.DataFrame({
'docno':
['1', '2', '3'],
'url':
['url1', 'url2', 'url3'],
'text':
['He ran out of money, so he had to stop playing',
'The waves were crashing on the shore; it was a',
'The body may perhaps compensates for the loss']
})
```

docno	url	text
1	url1	He ran out of money, so he had to stop playing
2	url2	The waves were crashing on the shore; it was a
3	url3	The body may perhaps compensates for the loss

```
pd_indexer = pt.DFIndexer("./pd_index")
# Add metadata fields as Pandas.Series objects, with the
# name of the Series object becoming the name of the meta field.
indexref = pd_indexer.index(df["text"], df["docno"])
```

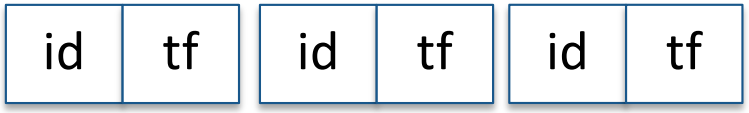
This creates a directory called ‘pd_index’ with files for the various index data structures

```
data.direct.bf
data.document.fsarrayfile
data.inverted.bf
data.lexicon.fsomapfile
data.lexicon.fsomaphash
data.lexicon.fsomapid
data.meta-0.fsomapfile
data.meta.idx
data.meta.zdata
data.properties
```

Index Configurations

Record positions to allow proximity/phrase search by adding `blocks=True` to the constructor

`PostingIndex (inverted)`

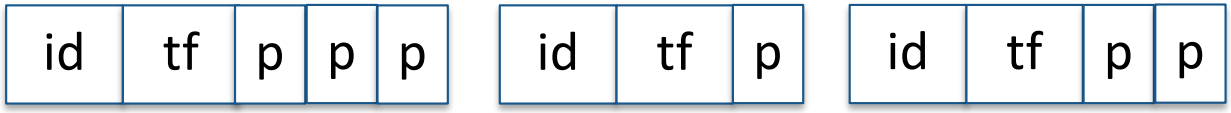


No positions

Positions

(more space)

`PostingIndex (inverted)`



Document metadata can be stored in the MetaIndex

- E.g. saving the raw document text can be useful for neural re-rankers
- Minimum/default: “docno” a unique string identifier for each document
- Recording more metadata takes more space and can slow down retrieval
- How these are sourced depends on the particular indexer

`MetaIndex`

Indexers and IndexingTypes

Indexers are utility classes in PyTerrier defining how we pass documents to be indexed by Terrier:

- pt.**DFIndexer** – index a dataframe
- pt.**TRECCollectionIndexer** – index files formatted in TREC or WARC (ClueWeb) format
- pt.**FilesIndexer** – index files of HTML, Word, PDF TXT etc.
- pt.**IterDictIndexer –** index iterable dictionaries (very similar to *streams* of dataframe rows)

PyTerrier will focus on this indexer in the future:
(1) multi-threading
(2) able to build into indexing pipelines *[part 2]*
(3) generic interface that other indexers (e.g. dense) can use *[part 4]*

IndexingTypes

- Classical – creates a direct index first, then inverts it. Default, but slower
- SinglePass – creates slices of inverted index in memory, then merges
- Memory – creates indices in memory

Overall aim – make it easy to make an index…

Datasets

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There are now a plethora of test collections

- Some document datasets require a license/agreement
  - e.g. Some TREC corpora such as Disks 4 & 5; GOV2; ClueWeb*xx*
- Topics/qrels are distributed over the web
  - They can be burdensome to find

Moreover, often we are using experimental environments with ephemeral storage – e.g. Google Colab

PyTerrier's datasets API provides downloading of queries, relevance assessments (aka qrels) & corpus documents, e.g.

```
dataset = pt.get_dataset('irds:cord19/trec-covid')
pt.IterDictIndexer('./index').index(dataset.get_corpus_iter())
```

Datasets (2)

PyTerrier has 128 datasets

- Full listing at

https://pyterrier.readthedocs.io/en/latest/datasets.html

Available Datasets

The table below lists the provided datasets, detailing the attributes available for each dataset. In each column, True designates the presence of a single artefact of that type, while a list denotes the available variants. Datasets with the `irds:` prefix are from the ir_datasets package; further documentation on these datasets can be found here.

dataset	corpus	index	topics	qrels
50pct		['ex1', 'ex2']	[training, validation]	[training,
antique	True		[train, test]	[train, tes
vaswani	True	True	True	True
trec-deep-learning-docs	True		[train, dev, test, test-2020, leaderboard-2020]	[train, dev
trec-deep-learning-passages	True		[train, dev, eval, test-2019, test-2020]	[train, dev

This includes 109 datasets from the `ir_datasets` package, developed by Sean and colleagues at AllenAI Inst.

- Prefixed by `irds:` in PyTerrier
- https://ir-datasets.com/

Dataset Index

✅ : Data available as automatic download

⚠️ : Data available from a third party

Dataset	docs	queries	qrels	scoreddocs	docpairs
antique	✅				
antique/test	✅	✅	✅		
antique/test/non-offensive	✅	✅	✅		
antique/train	✅	✅	✅		
antique/train/split200-train	✅	✅	✅		
antique/train/split200-valid	✅	✅	✅		
aquaint	⚠️				
aquaint/trec-robust-2005	⚠️	✅	✅		

Accessing Terrier Index Data Structures from Python

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How many documents does 'chemical' appear in?

Lexicon:

```
index.getLexicon()["chemic"].getDocumentFrequency()
```

What is the length of the 23rd document?

DocumentIndex

```
index.getDocumentIndex().getDocumentLength(22)
```

What documents contain 'chemical'?

Inverted Index

```
meta = index.getMetaIndex()
inv = index.getInvertedIndex()

le = lex.getLexiconEntry( "chemic" )
# the lexicon entry is also our pointer to access the inverted index posting list
for posting in inv.getPostings( le ):
    docno = meta.getItem("docno", posting.getId())
    print("%s with frequency %d " % (docno, posting.getFrequency()))
```

https://pyterrier.readthedocs.io/en/latest/terrier-index-api.html

Retrieval

Now we have an index, lets perform retrieval on it. We use a class called BatchRetrieve

- Don't let the name mislead you! It can also be used for single queries. We are renaming it to `TerrierRetrieve`…

```
br = pt.BatchRetrieve(index, wmodel="BM25")
```

We can search it

```
br.search("chemical reactions")
```

	qid	docid	docno	rank	score	query
0	1	251931	449027_8	0	11.954261	chemical reactions
1	1	251934	449027_11	1	11.091389	chemical reactions
2	1	251926	449027_3	2	11.087365	chemical reactions
3	1	36690	2769813_5	3	10.902714	chemical reactions

NB: There is also a AnseriniBatchRetrieve for retrieving from an Anserini index

Retrieving more than one query

For experiments, often we operate on more than one query. Lets say we have a dataframe of queries, `queryset`

```
queryset = pt.io.read_topics("./trec.topics")
```

queryset =

	qid	query
0	3990512	how can we get concentration onsomething
1	714612	why doesn t the water fall off earth if it s r...
2	2528767	how do i determine the charge of the iron ion ...

```
res = br.transform(queryset)
```

	qid	docid	docno	rank	score	query
0	3990512	173781	4366141_0	0	7.705589e+00	how can we get concentration onsomething
1	3990512	381364	3378079_2	1	7.485244e+00	how can we get concentration onsomething
2	3990512	269289	3270641_2	2	7.351503e+00	how can we get concentration onsomething
...	...	...	...	...	...	...
188628	1340574	291774	2489233_1	997	5.957036e+00	why do some people only go to church on easter...
188629	1340574	259693	3073253_4	998	5.955254e+00	why do some people only go to church on easter...
188630	1340574	265175	3610636_18	999	5.953573e+00	why do some people only go to church on easter...

In fact, the `transform()` method is used so often, it can be omitted

```
br(queryset)
```

Datasets also offer the topics as dataframes, ready to use

```
br(dataset.get_topics())
```

BatchRetrieve configurations

We expose most useful configuration through constructor arguments

```
pt.BatchRetrieve(index, wmodel="BM25")
```

Terrier has many such weighting models

- http://terrier.org/docs/current/javadoc/org/terrier/matching/models/package-summary.html
- Including TF_IDF, Divergence from Randomness models such as PL2, DPH, Dirichlet language model etc
- Also field-based models such as BM25F, PL2F

Other arguments:

- `controls` – other internal Terrier configuration
- `num_results` – how many results to retrieve
- `verbose` – display a progress bar
- `metadata` – what document metadata to export (default `["docno"]`)

Do we even need an index?

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Imagine our dataframe contains query and doc texts

```
pt.BatchRetrieve(index, metadata=["docno", "text"])
```

	qid	query	docno	text
0	q1	chemical reactions	d1	professor proton poured the chemicals
1	q1	chemical reactions	d2	chemical brothers turned up the beats

We can score that directly using a weighting model

```
Tfs = pt.text.scorer(wmodel="Tf")
Tfs.transform(query_docs)
```

	qid	docno	rank	score	query
0	q1	d1	0	1.0	chemical reactions
1	q1	d2	1	1.0	chemical reactions

```
BM25s = pt.text.scorer(wmodel="BM25", background_index=index)
BM25s.transform(query_docs)
```

	qid	docno	rank	score	query
0	q1	d1	0	13.823546	chemical reactions
1	q1	d2	1	13.823546	chemical reactions

These are like re-ranking operations – more on those later

Evaluating Pipelines

A basic experiment typically has 3 procedural steps:

- obtain the queries Q and the corresponding relevance assessments (qrels) RA
- transform those queries into results using the BatchRetrieve instance, let's say

  R = retrieve(Q)

- apply an evaluation tool, such as the ubiquitous `trec_eval` tool on RA and R (saved as as files?), to obtain effectiveness measures such as MAP or NDCG

This would need to be repeated for each retrieval instance

- And for loops are bad!

Also complex to compute things like number of queries improved, significance testing, etc.

An Experiment Abstraction

We define an Experiment abstraction, which performs an evaluation of multiple systems on queries Q and labels RA

```
pt.Experiment([br1, br2], Q, RA, [“map”, “ndcg”])
```

Returns a dataframe with measure values for each system

This is declarative in nature – we say what we want, not how to get it

- No for loops! ☺
- No writing files and then evaluating
- No longer dealing with results at all. Experiment does this for you – we have abstracted away from the results entirely

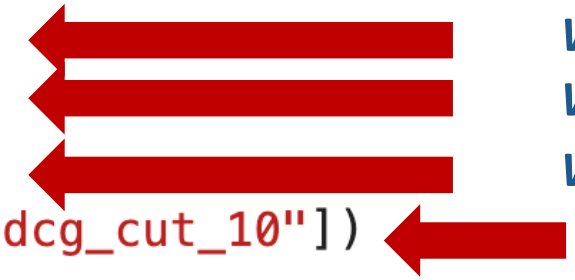
Internally, pt.Experiment uses `pytrec_eval`, which is a Python wrapper of `trec_eval`

van Gysel & de Rijke: Pytrec_eval: An Extremely Fast Python Interface to trec_eval. Proc. SIGIR 2018

Experiment Example

An example Experiment might look like

```
pt.Experiment(
    [tfidf, bm25],
    dataset.get_topics(),
    dataset.get_qrels(),
    eval_metrics=["map", "ndcg_cut_10"])
```



What are we evaluating?

What topics?

What qrels?

What measures? (trec_eval names)

This outputs a dataframe as follows:

	name	map	ndcg_cut_10
0	BR(TF_IDF)	0.290905	0.444411
1	BR(BM25)	0.296517	0.446609

Experiment Example, with more measures

If you are a trec_eval expert, "ndcg_cut_10" might make sense. For mere mortals…

```
from pyterrier.measures import *
pt.Experiment(
    [tfidf, bm25],
    dataset.get_topics(),
    dataset.get_qrels(),
    eval_metrics=[MAP, NDCG@10]
)
```

Import the available measures

Name the measure, @ cutoff

This outputs a dataframe as follows:

	name	AP	nDCG@10
0	BR(TF_IDF)	0.290905	0.444411
1	BR(BM25)	0.296517	0.446609

This is due to ir_measures – a more elegant evaluation tool by Sean. It wraps (py)trec_eval, ndeval, cwl_eval, etc..

ir_measures: https://ir-measur.es/ *cwl_eval: Azzopardi et al, SIGIR 2019*

Experiment Example, with names

We can put names in the output dataframe

```
pt.Experiment(
    [tfidf, bm25],
    dataset.get_topics(),
    dataset.get_qrels(),
    names=["TF.IDF", "BM25"],
    eval_metrics=["map", "ndcg_cut_10"])
```

Names of our approaches

Resulting output:

	name	map	ndcg_cut_10
0	TF.IDF	0.290905	0.444411
1	BM25	0.296517	0.446609

Experiments Variations (1)

Scientifically sound conclusions needs a baseline

- And significance testing

Declaring a baseline – specify the system you want to compare to

```
pt.Experiment(
    [tfidf, bm25],
    dataset.get_topics(),
    dataset.get_qrels(),
    names=["TF.IDF", "BM25"],
    baseline=0,
    eval_metrics=["map", "ndcg_cut_10"])
```

Index of the baseline system

	name	map	ndcg_cut_10	map +	map -	map p-value	ndcg_cut_10 +	ndcg_cut_10 -	ndcg_cut_10 p-value
0	TF.IDF	0.290905	0.444411	NaN	NaN	NaN	NaN	NaN	NaN
1	BM25	0.296517	0.446609	46.0	45.0	0.237317	16.0	23.0	0.63001

# of queries improved and degraded

P-value of two-tailed paired t-test

Repeated for each measure

Experiment Variations (2)

Lets add another model, say DPH, and compare with plain TF.IDF and BM25 again, with significance testing.

- This leads to the problem that the probabilities of the type I errors of the tests add up
- Increases likelihood of rejecting a true null hypothesis, i.e. declaring a significant difference when there actually is none

```
pt.Experiment(
    [tfidf, bm25, dph],
    dataset.get_topics(),
    dataset.get_qrels(),
    names=["TF.IDF", "BM25", "DPH"],
    baseline=0,
    correction='bonferroni', # or just 'b'
    eval_metrics=["map", "ndcg_cut_10"])
```

What correction method

	name	map	ndcg_cut_10	map +	map -	map p-value	map reject	map p-value corrected	ndcg_cut_10 +	ndcg_cut_10 -	ndcg_cut_10 p-value	ndcg_cut_10 reject	p-value corrected
0	TF.IDF	0.290905	0.444411	NaN	NaN	NaN	False	NaN	NaN	NaN	NaN	False	NaN
1	BM25	0.296517	0.446609	46.0	45.0	0.237317	False	0.711951	16.0	23.0	0.630010	False	1.0
							False	0.993016					1.0

Can null hypothesis be rejected (p<0.05) after correction

Corrected p-value

Norbert Fuhr: Proof by Experimentation? Towards Better IR Research. Proc. SIGIR 2020

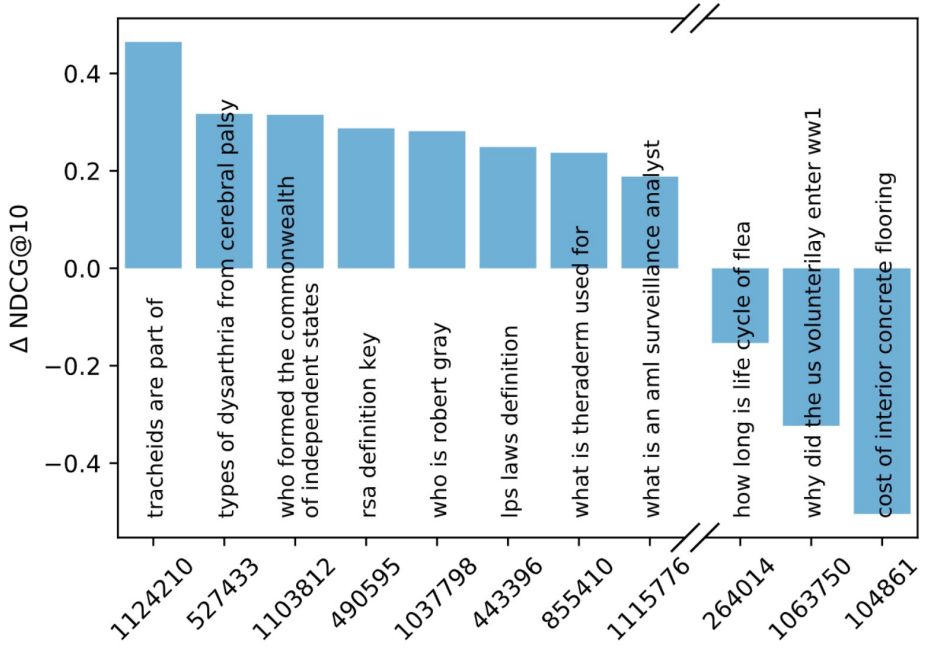
Experiment Variations (3)

Which queries were affected

```
pt.Experiment(
    [tfidf, bm25],
    dataset.get_topics(),
    dataset.get_qrels(),
    names=["TF.IDF", "BM25"],
    perquery=True,
    eval_metrics=["map", "ndcg_cut_10"])
```

Breakdown per query

	name	qid	measure	value
0	TF.IDF	1	map	0.268860
1	TF.IDF	1	ndcg_cut_10	0.573690
2	TF.IDF	2	map	0.056448
3	TF.IDF	2	ndcg_cut_10	0.094788



Experiment Variations (4)

Comparing to saved results

- Use `pt.io.write_results()` and `pt.io.read_results()`

```
pt.io.write_results(tfidf(dataset.get_topics()), "tfidf.res")

baselineDF = pt.io.read_results("tfidf.res")

pt.Experiment(
    [baselineDF, bm25],
    dataset.get_topics(),
    dataset.get_qrels(),
    names=["baseline DF", "BM25"],
    eval_metrics=["map", "ndcg_cut_10"])
```

A results dataframe can be directly passed to pt.Experiment

Useful for large collections or complex retrieval mechanisms

https://pyterrier.readthedocs.io/en/latest/experiments.html

Standard Indices – the Terrier Data Repository

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For common corpora (e.g. TREC-Covid, MSMARCO), we provide standard indices, which can be downloaded and instantiated in a single-line:

```
bm25_terrier_stemmed = pt.BatchRetrieve.from_dataset(
 'msmarco_passage', 'terrier_stemmed',
 wmodel='BM25')
```

use .from_dataset()

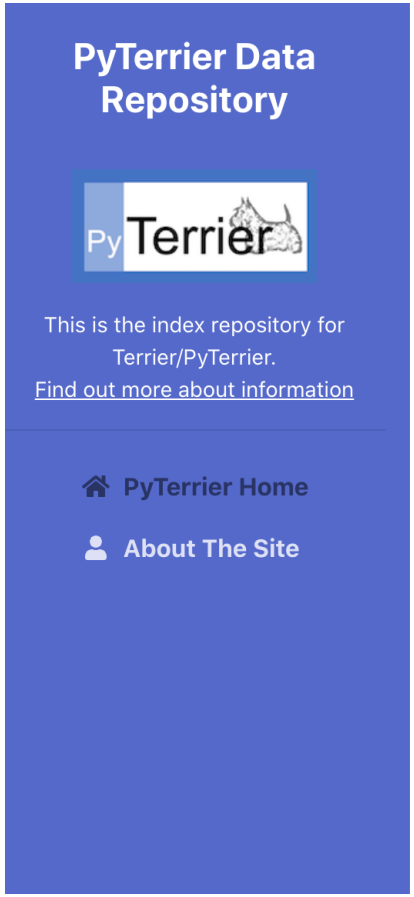
Name the dataset and index variant

Any more args for BatchRetrieve?

The Terrier Data Repository (http://data.terrier.org/) contains listings of indices. E.g. for MSMARCO passage corpus, we provide:

- 6 indices: terrier_stemmed, terrier_stemmed_deepct, terrier_stemmed_docT5query, terrier_stemmed_text, terrier_unstemmed, terrier_unstemmed_text, ance
- Snippets of code to use each index, including with BERT-based re-rankers
- Notebook reproducing baseline results, including pt.Experiment() configurations

Terrier Data Repository



Prebuilt indices for seven common datasets
For each dataset, various indices are provided

Terrier Data Repository

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terrier_stemmed_text

Last Update 2021-09-27 • 9.6GB

Terrier's default Porter stemming, and stopwords removed. Text is also saved in the MetaIndex to facilitate BERT-based reranking.

Browse index

Use this for retrieval in PyTerrier:

```
#!pip install git+https://github.com/Georgetown-IR-Lab/OpenNIR.git

import onir_pt

# Lets use a Vanilla BERT ranker from OpenNIR. We'll use the Capreolus model available from Huggingface

vanilla_bert = onir_pt.reranker('hgf4_joint',  text_field='body', ranker_config={'model': 'Capreolus/bert-ba

bm25_bert_terrier_stemmed_text = (
    pt.BatchRetrieve.from_dataset('msmarco_document', 'terrier_stemmed_text', wmodel='BM25', metadata=['docn
    >> pt.text.sliding(length=128, stride=64, prepend_attr='title')
    >> vanilla_bert
    >> pt.text.max_passage())
```

Code snippets to instantiate retrieval pipelines using various index variants

Terrier Data Repository

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Evaluation on trec-2019 topics and qrels

43 topics used in the TREC Deep Learning track Passage Ranking task, with deep judgements

```
pt.Experiment(
    [bm25_terrier_stemmed, dph_terrier_stemmed, bm25_terrier_stemmed_text, bm25_bert_terrier_stemmed_text, bm25_terrie
r_stemmed_docT5query, bm25_terrier_stemmed_deepct],
    pt.get_dataset('msmarco_passage').get_topics('test-2019'),
    pt.get_dataset('msmarco_passage').get_qrels('test-2019'),
    batch_size=200,
    filter_by_qrels=True,
    eval_metrics=[RR(rel=2), nDCG@10, nDCG@100, AP(rel=2)],
    names=['bm25_terrier_stemmed', 'dph_terrier_stemmed', 'bm25_terrier_stemmed_text', 'bm25_bert_terrier_stemmed_tex
t', 'bm25_terrier_stemmed_docT5query', 'bm25_terrier_stemmed_deepct'])
```

```
11:17:26.746 [main] WARN org.terrier.applications.batchquerying.TRECQuery - trec.encoding is not set; resorting to pl
atform default (ISO-8859-1). Retrieval may be platform dependent. Recommend trec.encoding=UTF-8
config file not found: config
[2021-09-23 11:19:03,772][onir_pt][DEBUG] using GPU (deterministic)
[2021-09-23 11:19:06,355][onir_pt][DEBUG] [starting] batches
```

```
[2021-09-23 11:22:36,997][onir_pt][DEBUG] [finished] batches: [03:31] [10502it] [49.86it/s]
```

	name	RR(rel=2)	nDCG@10	nDCG@100	AP(rel=2)
0	bm25_terrier_stemmed	0.641565	0.479540	0.487416	0.286448
1	dph_terrier_stemmed	0.667307	0.502513	0.485995	0.308977
2	bm25_terrier_stemmed_text	0.641565	0.479540	0.487416	0.286448
3	bm25_bert_terrier_stemmed_text	0.829457	0.685453	0.635066	0.444111
4	bm25_terrier_stemmed_docT5query	0.761370	0.630835	0.592220	0.404429
5	bm25_terrier_stemmed_deepct	0.689009	0.534393	0.521540	0.323135

Example notebooks to demonstrate reproducing results

In today's practical labs, we'll often be using the pre-built indices for TREC-Covid

Not just Terrier – Anserini & Pisa too

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In particular, Pisa is a fast in-memory index retrieval backend, with state-of-the-art efficiency (e.g. BlockMaxWAND)

Indexing

```
# from a dataset
dataset = pt.get_dataset('irds:msmarco-passage')
index = PisaIndex('./msmarco-passage-pisa')
index.index(dataset.get_corpus_iter())
```

Retrieval

```
dph = index.dph()
bm25 = index.bm25(k1=1.2, b=0.4)
pl2 = index.pl2(c=1.0)
qld = index.qld(mu=1000.)
```

A complex toolkit is made more accessible through PyTerrier

https://github.com/terrierteam/pyterrier_pisa

Round Up

We have reviewed the classical IR infrastructure, as implemented by PyTerrier, namely:

- Indexing, including datasets, accessing an index
- Retrieval & Evaluation

Next, you can use the provided Part 1 notebook to experience this infrastructure using the TREC Covid19 test collection

Coming Next: You have seen two retrieval objects: `BatchRetrieve` and `pt.text.scorer()`. These are two transformers

- They *transform* a dataframe into another dataframe
- In part 2, we'll generalise what we have seen into different types of transformers, and show how to combine them

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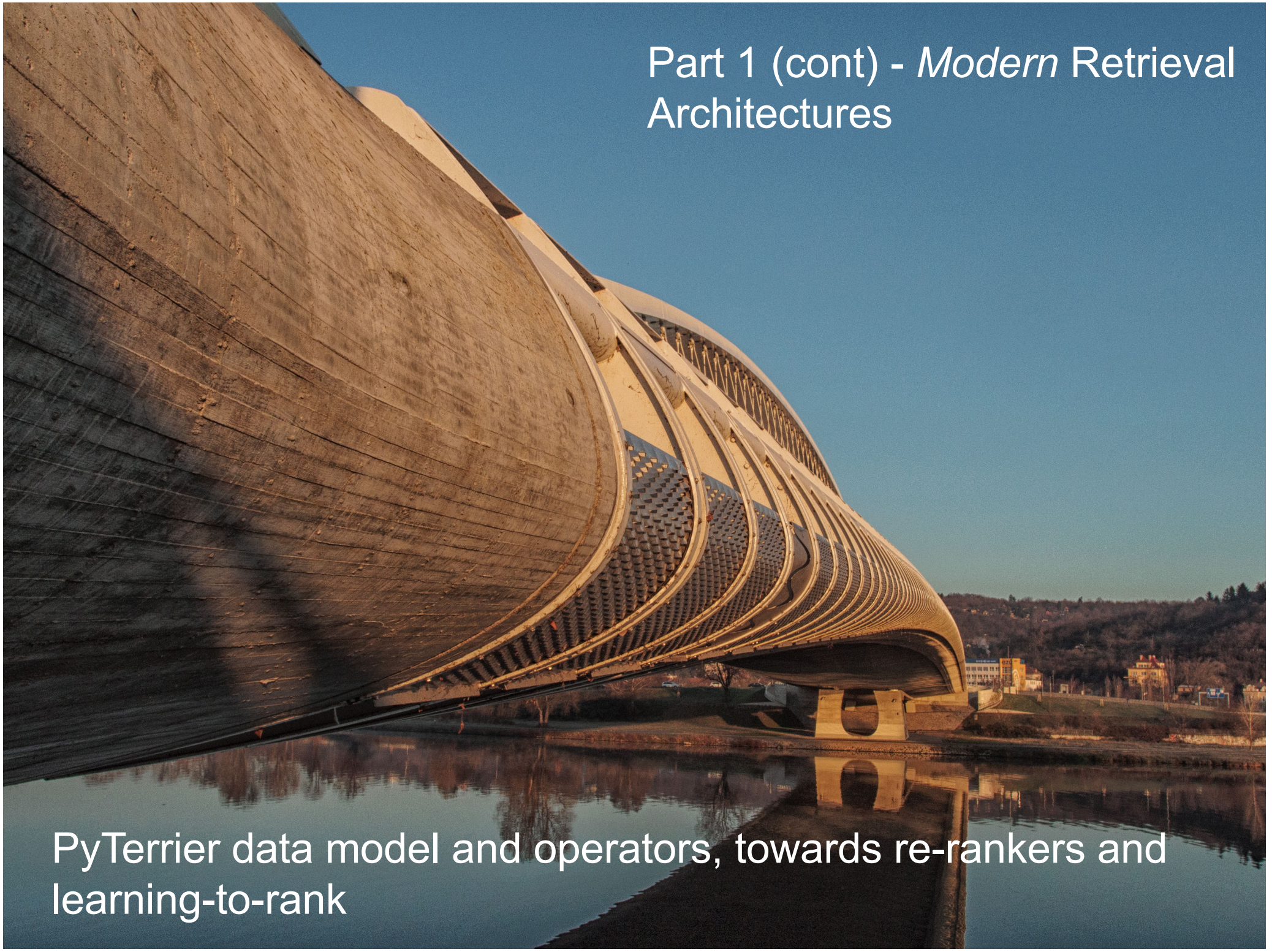
QUESTIONS?

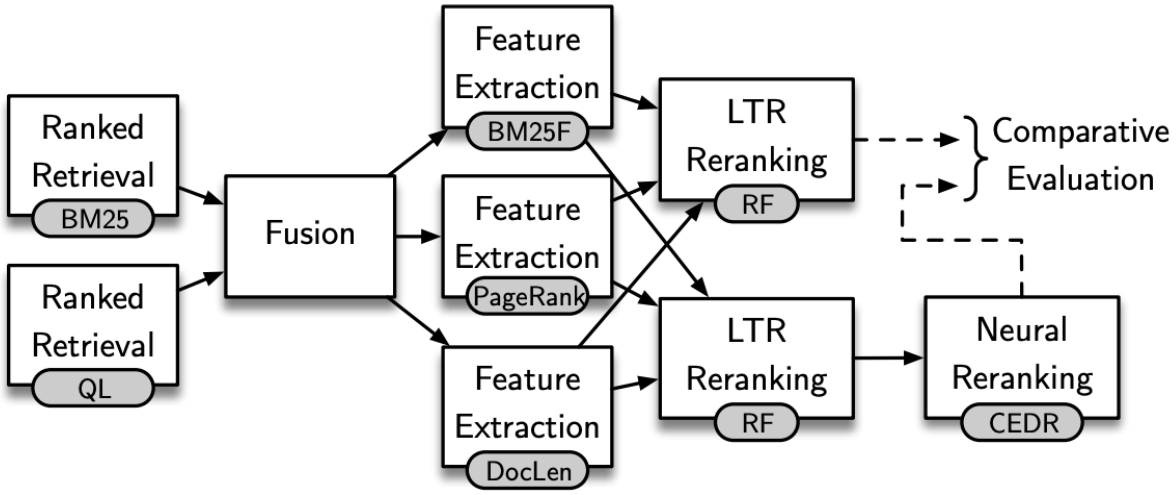

Part 1 (cont) - *Modern* Retrieval Architectures
PyTerrier data model and operators, towards re-rankers and learning-to-rank

Bridging to Modern Retrieval Architectures

In Classical Retrieval, we saw how to perform an experiment in a declarative manner, and perform simple retrievals

Actually, in IR, we have many retrieval and re-ranking components

Working with and combining result files to allow comparing complex ranking *pipelines* is tricky:



In Part 2, we generalise the architecture that has been seen into the PyTerrier data model and operators, to make it easy to build complex ranking pipelines

Modern Ranking Pipelines

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By using PyTerrier transformers and operators, we show that can easily express complex ranking pipelines in a conceptual & declarative way

Furthermore, we review modern techniques that fit into such ranking pipelines – such as…

- Query rewriting & pseudo-relevance feedback
- Learning to Rank

… and demonstrate how they can be implemented and extended within the PyTerrier framework

Finally, we also discuss the usefulness of PyTerrier for teaching IR

ILOs for this Session

ILO 1D. Understand modern retrieval architectures, such as re-rankers and ranking pipelines incorporating learning-to-rank strategies.

ILO 1E. Understand how different ranking and re-ranking operations can be *composed* to make more complex ranking models, in a declarative manner and leveraging a specific data model.

ILO 1F. Perform retrieval experiments within a Python notebook, including use of different features and learning-to-rank

Outline of Remainder of Morning

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PyTerrier data model & transformers

Coffee break

Learning to Rank

Wrap up and move to practical session

PYTERRIER DATA MODEL AND TRANSFORMERS

PyTerrier makes it easy to construct complex IR pipelines

Key components:

- **A common data model**
- **A rich library of transformation functions**
  including classical retrieval, dense retrieval, LTR, neural re-ranking
- **Operators to combine transformers**

Common Data Model

Q

qid	query
0	gold coast temperature november
1	one way flight to gold coast price
…	…

D

docno	text	title
0	Science & Mathematics Physi…	The hot glowing…
1	School-Age Kids Growth &…	Developmental…
…	…	…

R

qid	query	docno	score
0	gold coast temperature november	15213	0.5134
0	gold coast temperature november	42635	0.3742
0	gold coast temperature november	26340	0.3223
…	…	…	…

$R \subset Q \times D$

✓
✖

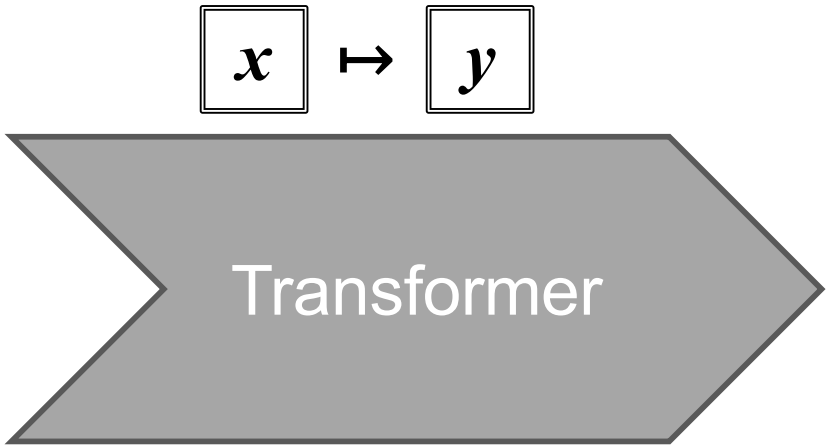
RA

qid	docno	label
0	15213	1
…	…	…

$RA \subset Q \times D$

(All of these are Pandas dataframes, i.e. relations)

Transformation Function Objects (Transformers)



Transformation Function Objects (Transformers)

$Q \mapsto R$

qid	query
0	gold coast temperature…
1	one way flight to gold…
…	…

BM25

Inverted Index

k1=1.2 b=0.75

qid	query	docno	score
0	gold coast…	15213	0.5134
0	gold coast…	42635	0.3742
0	gold coast…	26340	0.3223
…	…	…	…

Transformation Function Objects (Transformers)

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$$\boxed{Q} \mapsto \boxed{R}$$

qid	query
0	gold coast temperature…
1	one way flight to gold…
…	…

Your latest retrieval approach…

qid	query	docno	score
0	gold coast…	43242	0.1252
0	gold coast…	13746	0.1196
0	gold coast…	86454	0.0934
…	…	…	…

Transformation Function Objects (Transformers)

Transformer Class	Examples
$\boxed{\mathbf{Q}} \mapsto \boxed{\mathbf{R}}$ Retrieval	BM25, ColBERT, ANCE (dense retrieval)

Transformation Function Objects (Transformers)

Transformer Class	Examples
$\mathbf{Q} \mapsto \mathbf{R}$ Retrieval	BM25, ColBERT, ANCE (dense retrieval)
$\mathbf{R} \mapsto \mathbf{Q}$ Query Expansion	RM3, Bo1, etc.

Transformation Function Objects (Transformers)

Transformer Class	Examples
$\mathbf{Q} \mapsto \mathbf{R}$ Retrieval	BM25, ColBERT, ANCE (dense retrieval)
$\mathbf{R} \mapsto \mathbf{Q}$ Query Expansion	RM3, Bo1, etc.
$\mathbf{R} \mapsto \mathbf{R}$ Re-ranking	Vanilla BERT, monoT5, etc.
$\mathbf{Q} \mapsto \mathbf{Q}$ Query Re-writing	SDM, IntenT5, etc.

```
[12] index = pt.IndexRef.of('./cord19-index')
     bm25 = pt.TerrierRetrieve(index, wmodel='BM25')

     bm25(topics)
```

	qid	docid	docno	rank	score	query
0	1	83032	dv9m19yk	0	11.865104	what is the origin of covid 19
1	1	109719	kgifmjvb	1	11.412908	what is the origin of covid 19
2	1	135553	wmfcey6f	2	11.397281	what is the origin of covid 19
3	1	68472	4dtk1kyh	3	10.805808	what is the origin of covid 19
4	1	114244	cniyembt	4	10.763978	what is the origin of covid 19
...	...	...	...	...	...	...
49995	50	146581	2o8u4eny	995	17.073736	what is known about an mrna vaccine for the sa...
49996	50	76091	fayr38c7	996	17.071367	what is known about an mrna vaccine for the sa...
49997	50	102986	jlrk8fg0	997	17.070633	what is known about an mrna vaccine for the sa...
49998	50	183502	imwa033f	998	17.070633	what is known about an mrna vaccine for the sa...
49999	50	95511	j5j3hxxw	999	17.070486	what is known about an mrna vaccine for the sa...

R

BM25 Results

```
[22] rm3 = pt.rewrite.RM3(index)

     rm3(bm25(topics))
```

	qid	query	query_0
0	1	19^0.200000018 origin^0.325867474 covid^0.2000...	what is the origin of covid 19
1	10	19^0.085714296 across^0.019867204 epidem^0.029...	has social distancing had an impact on slowing...
2	11	walk^0.030252097 urolog^0.042577028 optim^0.04...	what are the guidelines for triaging patients ...
3	12	older^0.041744966 best^0.100000009 quarantin^0...	what are best practices in hospitals and at ho...
4	13	contact^0.026820807 possibl^0.021502888 outbre...	what are the transmission routes of coronavirus
5	14	centuri^0.020000001 manag^0.020000001 contain^...	what evidence is there related to covid 19 sup...
6	15	bodi^0.167176828 can^0.120000005 cold^0.034101...	how long can the coronavirus live outside the ...
7	16	stabl^0.152924821 dai^0.042988449 surfac^0.218...	how long does coronavirus remain stable on sur...

Q

Expanded query

Original query

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R

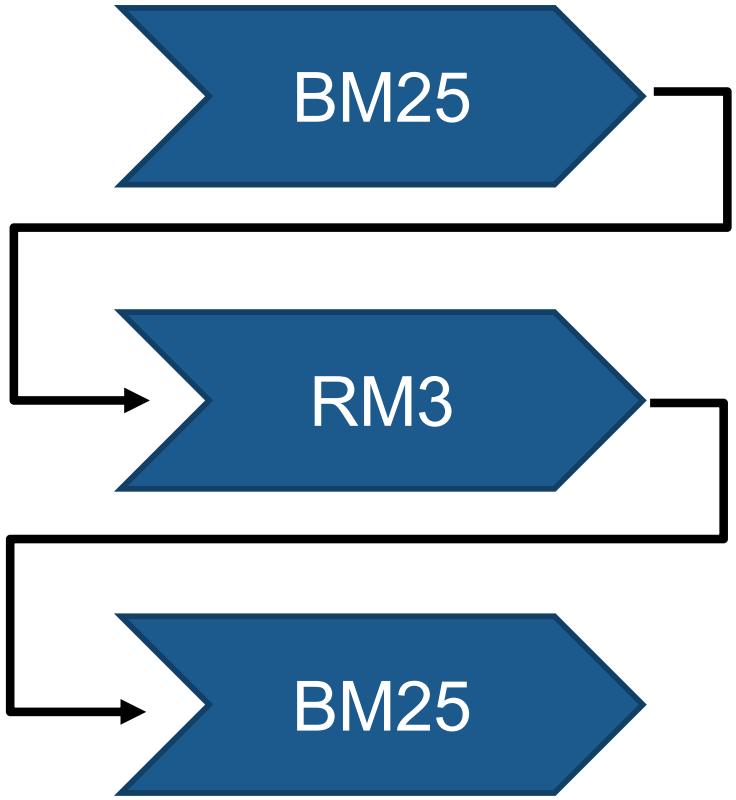
```
[23] bm25(rm3(bm25(topics)))
```

	qid	docid	docno	rank	score	query	query_0
0	1	109719	kgifmjvb	0	19.316403	19^0.200000018 origin^0.325867474 covid^0.2000...	what is the origin of covid 19
1	1	135553	wmfcey6f	1	19.281917	19^0.200000018 origin^0.325867474 covid^0.2000...	what is the origin of covid 19
2	1	83032	dv9m19yk	2	11.101417	19^0.200000018 origin^0.325867474 covid^0.2000...	what is the origin of covid 19
3	1	103317	ec8lpgl3	3	11.044733	19^0.200000018 origin^0.325867474 covid^0.2000...	what is the origin of covid 19
4	1	114244	cniyembt	4	10.865901	19^0.200000018 origin^0.325867474 covid^0.2000...	what is the origin of covid 19
...	...	...	...	...	...	...	...
49995	9	164232	6djfpvz7	995	6.987903	19^0.150000006 covid^0.150000006 mp^0.05102380...	how has covid 19 affected canada
49996	9	68116	6k8vedy3	996	6.983706	19^0.150000006 covid^0.150000006 mp^0.05102380...	how has covid 19 affected canada
49997	9	132455	9z0azq8y	997	6.983706	19^0.150000006 covid^0.150000006 mp^0.05102380...	how has covid 19 affected canada
49998	9	132456	wfss2j7v	998	6.983706	19^0.150000006 covid^0.150000006 mp^0.05102380...	how has covid 19 affected canada
49999	9	163423	n76892ur	999	6.981468	19^0.150000006 covid^0.150000006 mp^0.05102380...	how has covid 19 affected canada

Results of BM25 over RM3

Operators

```
bm25(rm3(bm25(topics)))
```

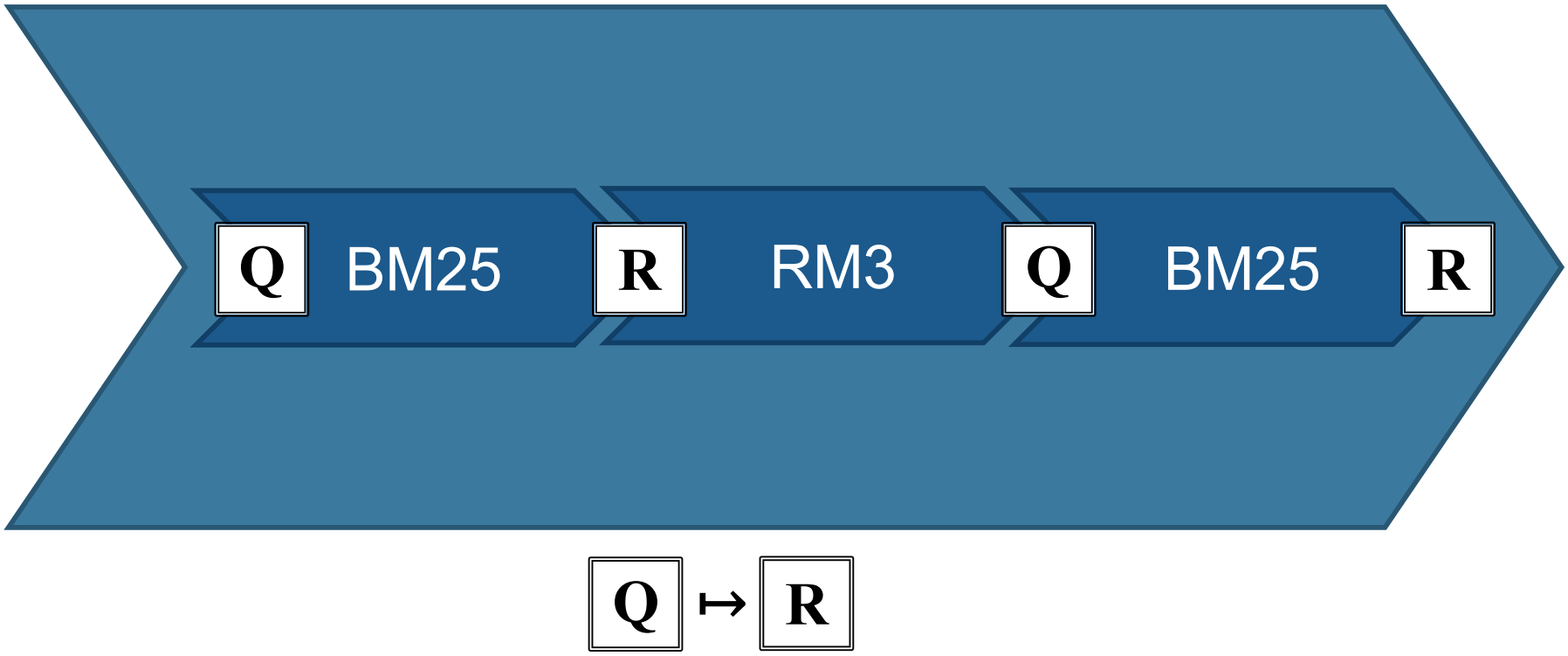


Operators

A better way: the “then” operator

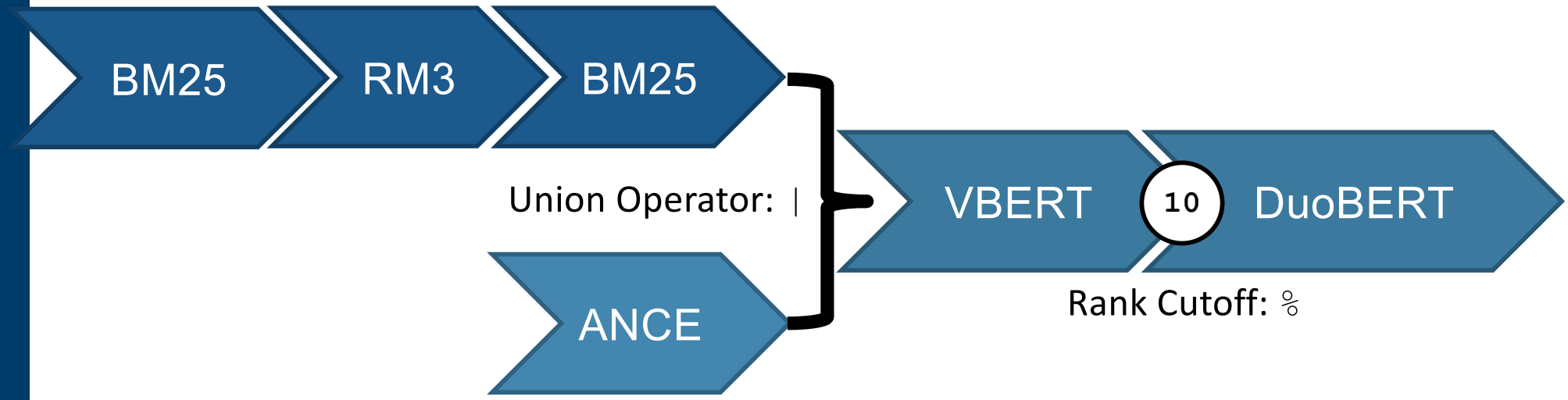
```
A >> B (A then B)
```

```
pipeline = bm25 >> rm3 >> bm25
```



Operators

```
pipeline =    bm25 >> rm3 >> bm25
```



Other operators available, including caching, linear score combination, etc.

Transformer Operators

PyTerrier defines a suite of operators on transformers

Op.	Name	Description
>>	*then (composition)*	Pass the output from one transformer to the next transformer
+	*linear combine*	Sum the query-document scores of the two retrieved results lists
*	*scalar product*	Multiply the query-document scores of a retrieved results list by a scalar
**	*feature union*	Combine two retrieved results lists as features
|	*set union*	Make the set union of documents from the two retrieved results lists
&	*set intersection*	Make the set intersection of the two retrieved results lists
%	*rank cutoff*	Shorten a retrieved results list to the first K elements
^	*concatenate*	Add the retrieved results list from one transformer to the bottom of the other

Our ICTIR 2020 paper on PyTerrier provides relational algebra semantics for each operator

- Let's look at a few others…

Lets look at some retrieval use cases

1. Linear Combinations

```
linear = 2 * pt.BatchRetrieve(index, wmodel="BM25")
       + 3 * pt.BatchRetrieve(index, wmodel="DPH")
```

Final Output Type: R

Output Types: R

2. Sequential Dependence Model (proximity)

```
sdm = pt.rewrite.SequentialDependence() >> bm25
```

Input Type: Q

Output Type: Q

Output Type: R

	qid	query
0	1	chemical reactions

	qid	query
0	1	chemical reactions #combine:0=0.1:wmodel=org.terrier.matching.models.dependence.pBiL(#1(chemical reactions)) #combine:0=0.1:wmodel=org.terrier.matching.models.dependence.pBiL(#uw8(chemical reactions)) #combine:0=0.1:wmodel=org.terrier.matching.models.dependence.pBiL(#uw12(chemical reactions))

Lets look at some retrieval use cases

1. Linear Combinations

```
linear = 2 * pt.BatchRetrieve(index, wmodel="BM25")
       + 3 * pt.BatchRetrieve(index, wmodel="DPH")
```

Final Output Type: R

Output Types: R

2. Sequential Dependence Model (proximity)

```
sdm = pt.rewrite.SequentialDependence() >> bm25
```

Input Type: Q

Output Type: Q

Output Type: R

3. Pseudo-relevance feedback (QE)

```
rm3 = bm25 >> pt.rewrite.RM3(index) >> bm25
```

Output Type: R

Output Type: Q

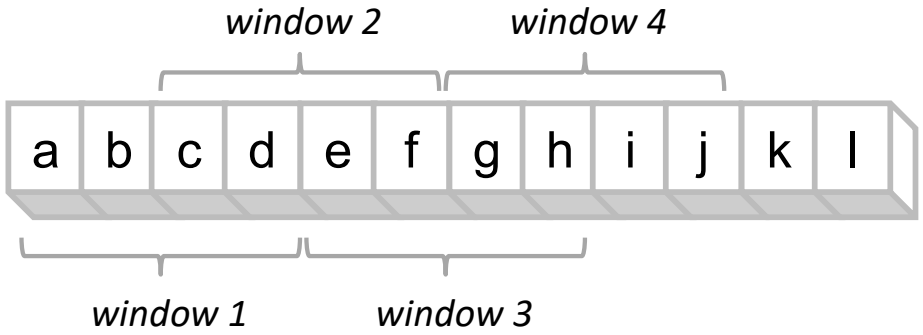
Output Type: R

Retrieval Use Case: Passaging

Some long documents may only contain a relevant passage about the query

- In such cases, passage-based retrieval can benefit effectiveness
- Its also useful for neural models that do not scale efficiently to long documents [c.f. Part 2]

For instance, applying a sliding window over the text of the document to get passages, and scoring each passage individually



Window size 4
Window stride 2

- Some settings benefit from prepending the title to each passage

[Dai & Callan, SIGIR 2018]

Retrieval Use Case: Passaging

Lets try this out:

```
Bm25maxp = pt.BatchRetrieve(index, wmodel="BM25", metadata=["docno", "text"])
         >> pt.text.sliding("text", length=150, stride=75)
         >> pt.text.scorer(wmodel="BM25")
         >> pt.text.max_passage()
```

BR output (R w/ text)

qid	docno	text
q1	d1	a b c d

sliding("text", 2, 1) output

qid	docno	text
q1	d1%p1	a b
q1	d1%p2	b c
q1	d1%p3	c d

textscorer output (R)

qid	docno	rank	score
q1	d1%p5	0	5.0
q1	d2%p4	1	4.0
q1	d1%p3	2	3.0
q1	d1%p1	3	1.0

max_passage output

qid	docno	rank	score
q1	d1	0	5.0
q1	d2	1	4.0

(Some attributes omitted for brevity, e.g. query)

Of course, we could change `pt.text.scorer()` to be a more advanced approach, e.g. BERT-based neural re-ranker [Part 2]

Indexing Pipelines

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Applying passaging during retrieval can be expensive

- Can it be applied at indexing time?
- There are also other techniques that we will see in Part 3 (e.g. DeepCT, doc2query) that can be applied at indexing time

The >> operator can also be applied to create indexing pipelines

Hence, a MaxPassage retrieval can also be achieved as follows

```
indexer = pt.text.sliding("text", length=150, stride=75)
        >> pt.IterDictIndexer()
indexref = indexer.index(dataset.get_corpus_iter())
MaxP = pt.BatchRetrieve(indexref, wmodel="BM25")
     >> pt.text.max_passage()
```

Note that while transformers operate on a dataframes, we might not fit an entire corpus into a dataframe

- Hence indexing pipelines perform transparent batching of documents

Transformer Implementations (1/2)

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All transformers implement a base class called pt.Transformer

- This has all the methods to support operator overloading, e.g. `__add__()`, `__rshift__()`

However, creating your own transformer is easy using `pt.apply` functions. These create a new transformer from your own function

- For instance, to rewrite a query – `pt.apply.query()`

```
# this will remove pre-defined stopwords from the query
stops=set(["and", "the"])

# a naieve function to remove stopwords
def _remove_stops(q):
    terms = q["query"].split(" ")
    terms = [t for t in terms if not t in stops ]
    return " ".join(terms)

# a query rewriting transformer applying _remove_stops
p1 = pt.apply.query(_remove_stops) >> pt.BatchRetrieve(index, wmodel="DPH")
```

- `pt.apply.query()` returns a transformer, which applies `_remove_stops` to each query. The previous query is saved in the query_0 attribute

Transformer Implementations (2/2): pt.apply.doc_score()

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`pt.apply.doc_score()` uses a function that returns a score

```
# this transformer will subtract the number of character in the query
# from the score of each retrieved document

p = pt.BatchRetrieve(index, wmodel="DPH") >>
    pt.apply.doc_score(lambda doc : doc["score"] - len(doc["query"]))
```

In this way, ANY function that can returns a number can be used for retrieval

- i.e. any (SOTA) approach that can be expressed as a function of the text of the document and the text of the query can easily be used as a re-ranker in PyTerrier

`pt.apply.doc_score()` & `pt.apply.query()` have known semantics

- There are also advanced "generic" apply functions that can apply an arbitrary change of a dataframe as a transformer

Worked Example – Reranking using SentenceTransformers

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Let's compare two BERT models for reranking BM25:

```
import pandas as pd
from sentence_transformers import CrossEncoder, SentenceTransformer
crossmodel = CrossEncoder('cross-encoder/ms-marco-MiniLM-L-12-v2', max_length=512)
bimodel = SentenceTransformer('paraphrase-MiniLM-L6-v2')

def _crossencoder_apply(df : pd.DataFrame):
    return crossmodel.predict(list(zip(df['query'].values, df['text'].values)))

cross_encT = pt.apply.doc_score(_crossencoder_apply, batch_size=128)

def _biencoder_apply(df : pd.DataFrame):
    from sentence_transformers.util import cos_sim
    query_embs = bimodel.encode(df['query'].values)
    doc_embs = bimodel.encode(df['text'].values)
    scores =  cos_sim(query_embs, doc_embs)
    return scores[0]

bi_encT = pt.apply.doc_score(_biencoder_apply, batch_size=128)

pt.Experiment(
    [ bm25, bm25 >> bi_encT, bm25 >> cross_encT ],
    dataset.get_topics(),
    dataset.get_qrels(),
    ["map"],
    names=["BM25", "BM25 >> BiEncoder", "BM25 >> CrossEncoder"]
)
```

Load CE & BE models

CE Apply function scores 128 queries and texts at once using CE

BE apply function scores 128 queries, and 128 texts, then computes Cos scores

Combine each with BM25, and evaluate

Worked Example – Reranking using SentenceTransformers

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Let's compare two BERT models for reranking BM25:

```
import pandas as pd
from sentence_transformers import CrossEncoder, SentenceTransformer
crossmodel = CrossEncoder('cross-encoder/ms-marco-MiniLM-L-12-v2', max_length=512)
bimodel = SentenceTransformer('paraphrase-MiniLM-L6-v2')

def _crossencoder_apply(df : pd.DataFrame):
    return crossmodel.predict(list(zip(df['query'].values
```

```
    dataset.get_qrels(),
    ["map"],
    names=["BM25", "BM25 >> BiEncoder", "BM25 >> CrossEncoder"]
)
```

	name	RR(rel=2)	nDCG@10	nDCG@100	AP(rel=2)
0	BM25	0.641565	0.479540	0.487416	0.286448
1	BM25 >> BiEncoder	0.793350	0.605352	0.549940	0.362597
2	BM25 >> CrossEncoder	0.914729	0.738378	0.669271	0.488546

https://github.com/terrier-org/pyterrier/blob/master/examples/notebooks/sentence_transformers.ipynb

Summary: PyTerrier Standard Transformers

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Retrieval

- `pt.BatchRetrieve()`

Query Rewriting/Expansion

- `pt.rewrite.SequentialDependence()`
- `pt.rewrite.RM3()`
- `pt.rewrite.Bo1QueryExpansion()`
- `pt.rewrite.KLQueryExpansion()`

Text

- `pt.text.get_text()`
- `pt.text.scorer()`
- `pt.text.sliding()`
- `pt.text.max_passage() first_passage() mean_passage() kmaxavg_passage()`

In Part 2B, we'll see learning-to-rank transformers

In Parts 3 & 4, we'll see more add-on transformers for neural re-ranking and end-to-end

Summary: PyTerrier Utility Transformers

Apply functions as pipelines

- `pt.apply.doc_score(_fn)`
- `pt.apply.query(_fn)`
- `pt.apply.generic(_fn)`
- `pt.apply.by_query(_fn)`
- `pt.apply.<ANY COLUMN NAME>(_fn)`

User-defined functions to change the pipeline in arbitrary ways

Inspect within a transformer pipeline

- `pt.debug.print_rows()`
- `pt.debug.print_columns()`
- `pt.debug.print_num_rows()`

Summary: PyTerrier Transformer Operators

Op.	Name	Description
>>	*then* (*composition*)	Pass the output from one transformer to the next transformer
+	*linear combine*	Sum the query-document scores of the two retrieved results lists
*	*scalar product*	Multiply the query-document scores of a retrieved results list by a scalar
**	*feature union*	Combine two retrieved results lists as features *(Part 2B)*
|	*set union*	Make the set union of documents from the two retrieved results lists
&	*set intersection*	Make the set intersection of the two retrieved results lists
%	*rank cutoff*	Shorten a retrieved results list to the first K elements
^	*concatenate*	Add the retrieved results list from one transformer to the bottom of the other

Reflections (1)

Transformers build on PyTerrier's extensible data model

- defined on IR-level objects: queries and documents
- We can add more data model columns for, e.g., ConvQA

Operators, defined with clear semantics, allow different transformers to be easily combined

- The structure of the pipeline implementations are close to their conceptual design
- This is all declarative in nature - we aren't **writing code** that iterates over any queries or documents (no for loops ☺!)

New techniques can be used and evaluated within a unified framework

- `pt.apply.doc_score()` can be easily applied to integrate new state-of-the-art approaches

Reflections (2)

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Thinking in this manner allows many techniques to be easily instantiated… and new techniques to be designed.

- We have created pipelines for integrating PRF into dense retrieval
- CIKM 2021 papers making advances on ColBERT are designed and implemented as variants of pipelines

```
import pyterrier_colbert.pruning

#CIKM 2021 Approximate Scoring paper: only retrieve 200 candidates for exact re-ranking
ann_pipe = (factory.ann_retrieve_score() % 200) >> factory.index_scorer(query_encoded=True)

#CIKM 2021 query embeddings paper: only keep the 9 tokens with highest ICF
qep_pipe5 = (factory.query_encoder()
            >> pyterrier_colbert.pruning.query_embedding_pruning(factory, 5)
            >> factory.set_retrieve(query_encoded=True)
            >> factory.index_scorer(query_encoded=False)
)
qep_pipe9 = (factory.query_encoder()
            >> pyterrier_colbert.pruning.query_embedding_pruning(factory, 9)
            >> factory.set_retrieve(query_encoded=True)
            >> factory.index_scorer(query_encoded=False)
)
```

Even if we have a single coherent end-to-end retrieval model, for deployment, we may need things like query-biased snippets, which are pipelined after retrieval…

Building your own

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We have been extending PyTerrier with "plugins" for various models - some you will seen in Parts 2 & 3:

- pyt_t5, pyt_colbert, pyt_ance, pyt_doc2query, pyt_splade

Its easy to make a retrieval function into a PyTerrier transformer:

- Make a class that extends `pt.Transformer`
- Define a `transform()` method that takes as input a dataframe and returns a dataframe
- `pt.apply` functions can reduce the boilerplate even further.

Indexers also can be supported

- Make a class that extends `pt.Indexer`
- Define an `index()` method that takes iterable of dicts each containing a document.

Then its plain sailing!

11:00-11:15

COFFEE BREAK

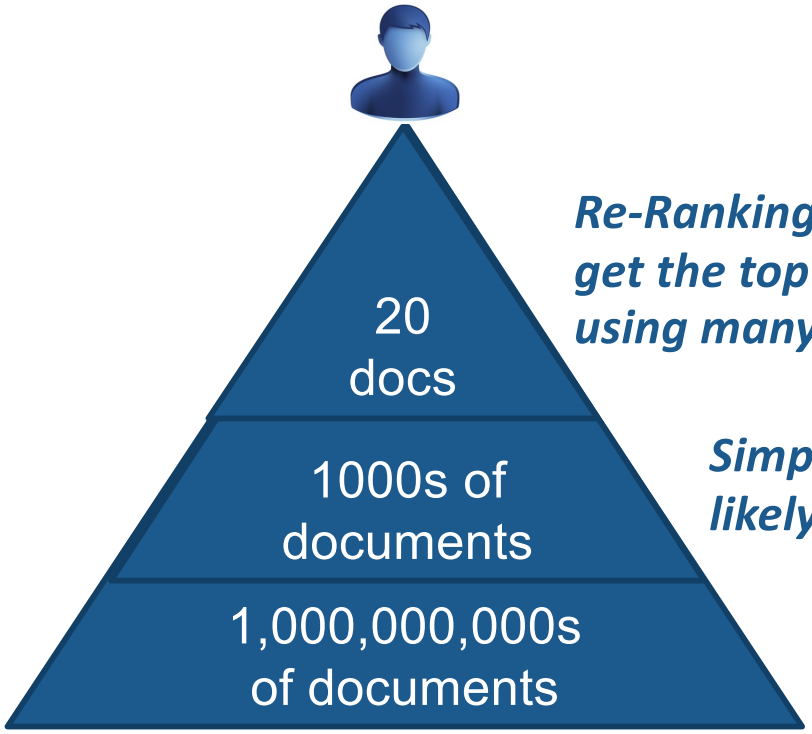
Part 1B

LEARNING TO RANK

Ranking Cascades

In many search scenarios, the ranking process can be seen as a series of cascades [1]

- Rank some documents
- Pass top-ranked onto next cascade for refined re-ranking



Re-Ranking: Try really hard to get the top of the ranking correct, using many signals (features) ⇨ ***LEARNING TO RANK Features & Models***

Simple Ranking: Identify a set most likely to contain relevant documents ⇨ ***e.g. BM25***

Boolean: Do query terms occur? ⇨ ***e.g. AND/OR /phrase***

[1] J Pederson. Query understanding at Bing. SIGIR 2010 Industry Day.

Motivations for Learning

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How to choose term weighting models?

- Term weighting models have different **assumptions** about how relevant documents should be retrieved

Also:

- **Proximity-models**: close co-occurrences matter more
- **Priors**: documents with particular lengths or URL/inlink distributions matter more
- **Field-based models**: term occurrences in different fields matter differently (e.g. BM25F, PL2F)
- ***Query Features:*** Long queries, difficult queries, query type

How to combine all these easily and appropriately?

Learning to Rank definition

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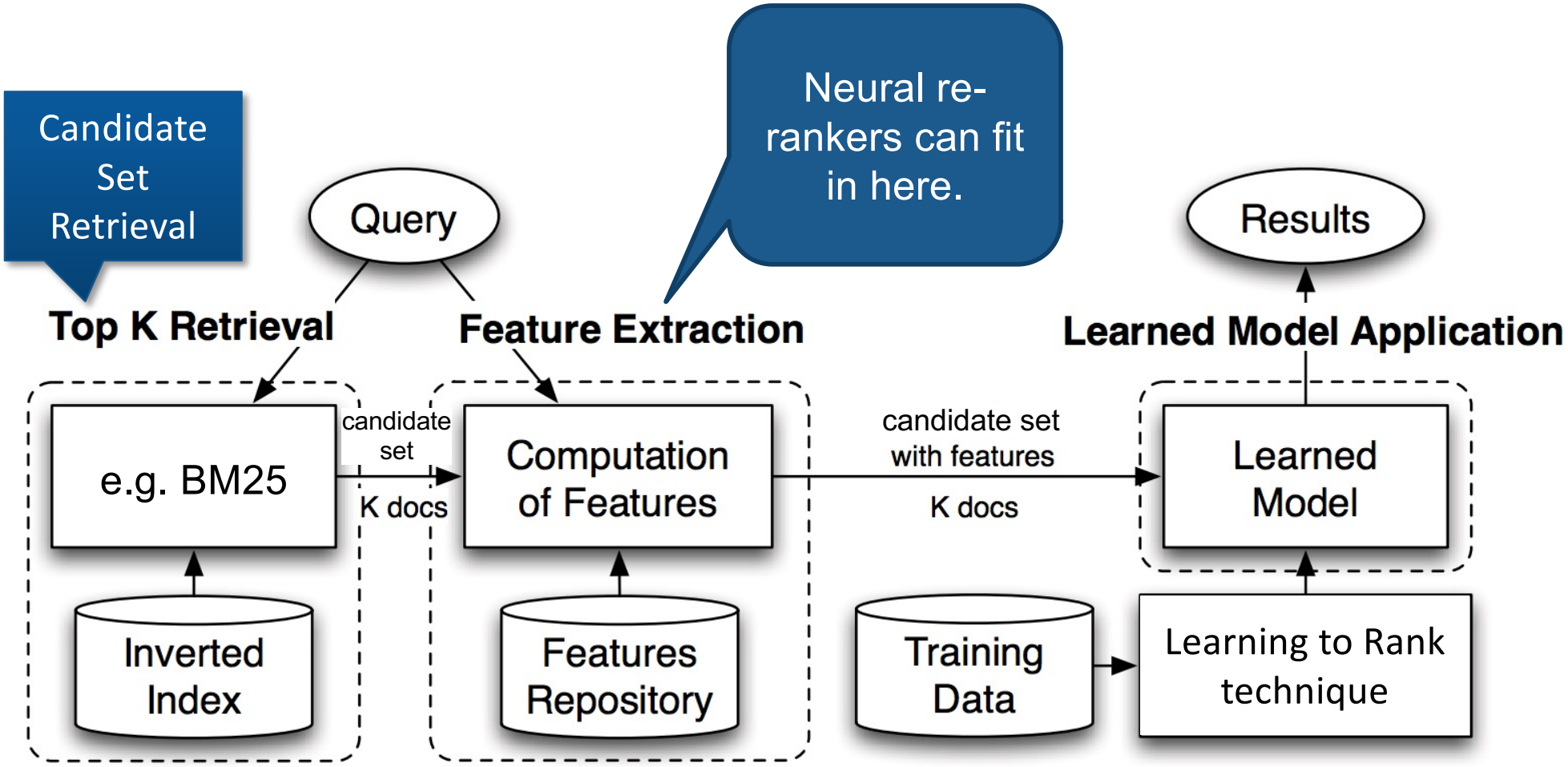
Learning to rank describes the application of tailored machine learning techniques, applied to re-rank a candidate set of retrieved documents

- This requires hand-engineered features (incl. weighting models) as relevance signals
- LTR techniques should focus on getting the top-ranked documents ranked correctly, using adapted loss functions:
  - Pointwise: e.g. regression – just tries to predict document label
  - Pairwise: tries to get pairs of documents with differing label correctly ranked
  - Listwise: tries to get most relevant document at top of ranking

Different model forms are popular: linear, trees, neural nets

LTR, Schematically…



N. Tonellotto, C. Macdonald, I. Ounis. (2013). Efficient and effective retrieval using selective pruning. WSDM'13.

Types of Features

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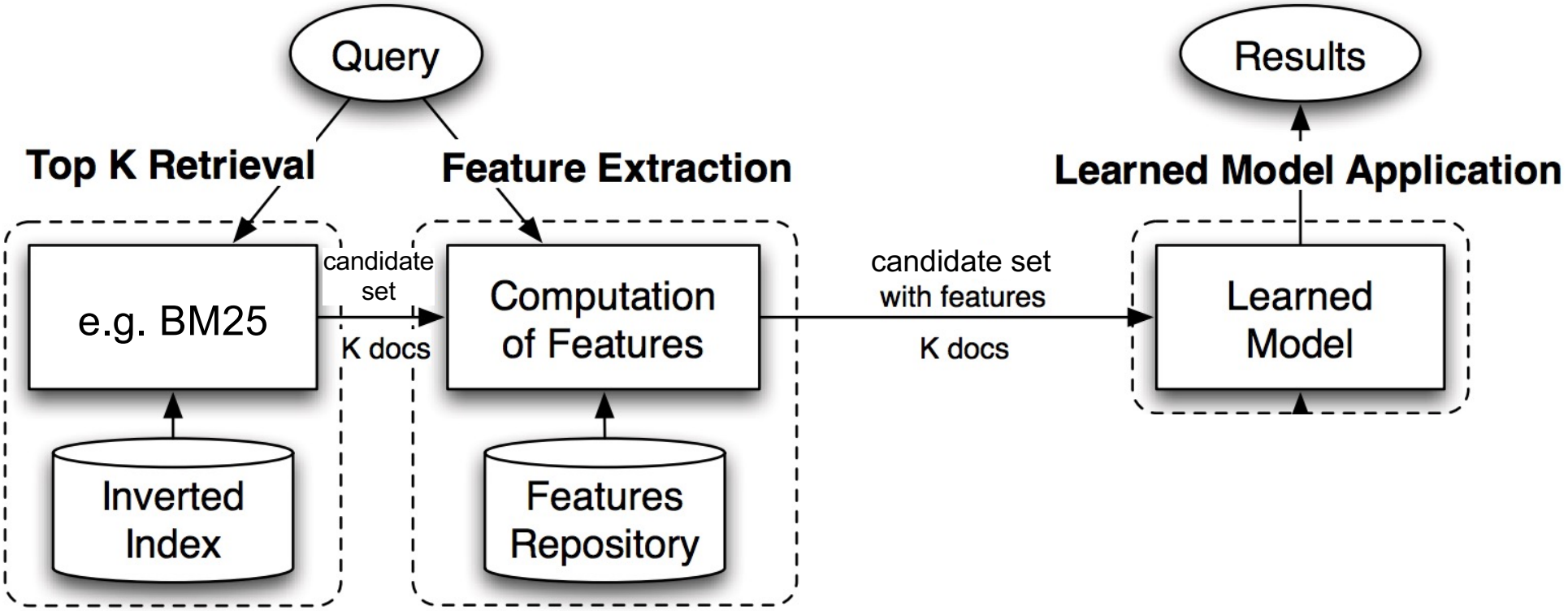
Typically, commercial search engines use hundreds of features for ranking documents, usually categorised as follows:

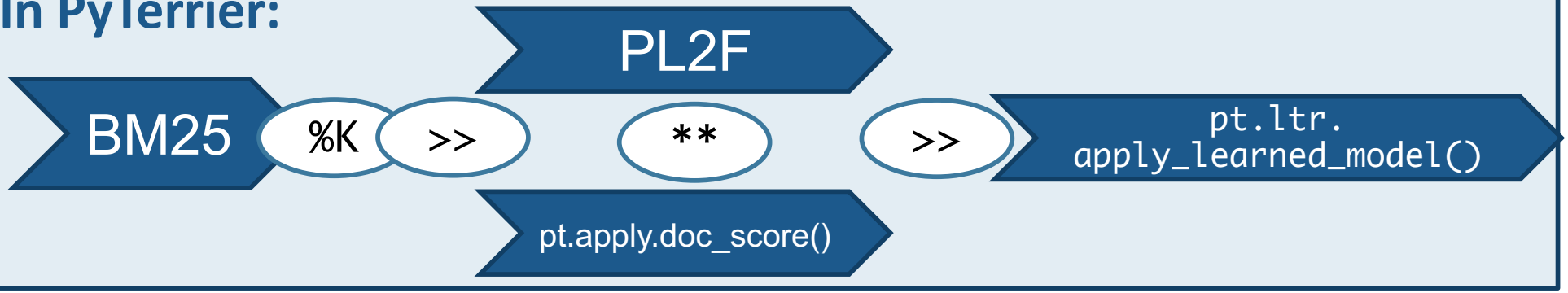
Name	Varies depending on…		Examples
	Query	Document	
Query Dependent Features	✓	✓	Weighting models, e.g. BM25, PL2 Proximity models, e.g. Markov Random Fields Field-based weighting models, e.g. PL2F Neural re-rankers [Part 3]
Query Independent Features	X	✓	PageRank, number of inlinks Spamminess
Query Features	✓	X	Query length, Query performance predictors Presence of entities

C. Macdonald et al. On the Usefulness of Query Features for Learning-to-Rank, CIKM 2012

Matching LTR concepts to PyTerrier…



In PyTerrier:



"Featured" Data Model

Retrieved documents with features, R_f:

qid	query	docno	score	rank	*features*

- The features column contains, for each document, an array of additional feature scores.
- These can be used for learning and applying LTR models
- Applying an LTR model would override the original score of the document, causing a re-ranking

Feature Union Operator

Feature Union (**)

- Say we want to take multiple retrieval approaches as different features. We use ** to denote, that given a set of input documents, use these transformers to obtain additional feature scores
- Formally:

$$Rf = (T_1 \ ** \ T_2)(R) :=$$
$$R_1 = T_1(R), \quad R_2 = T_2(R)$$
$$Rf = (R_1 \bowtie R_2)[[f_1, f_2] \rightarrow f]$$

- E.g.

```
BatchRetrieve("BM25") >>      ( BatchRetrieve("Tf") ** BatchRetrieve("PL2") )
```

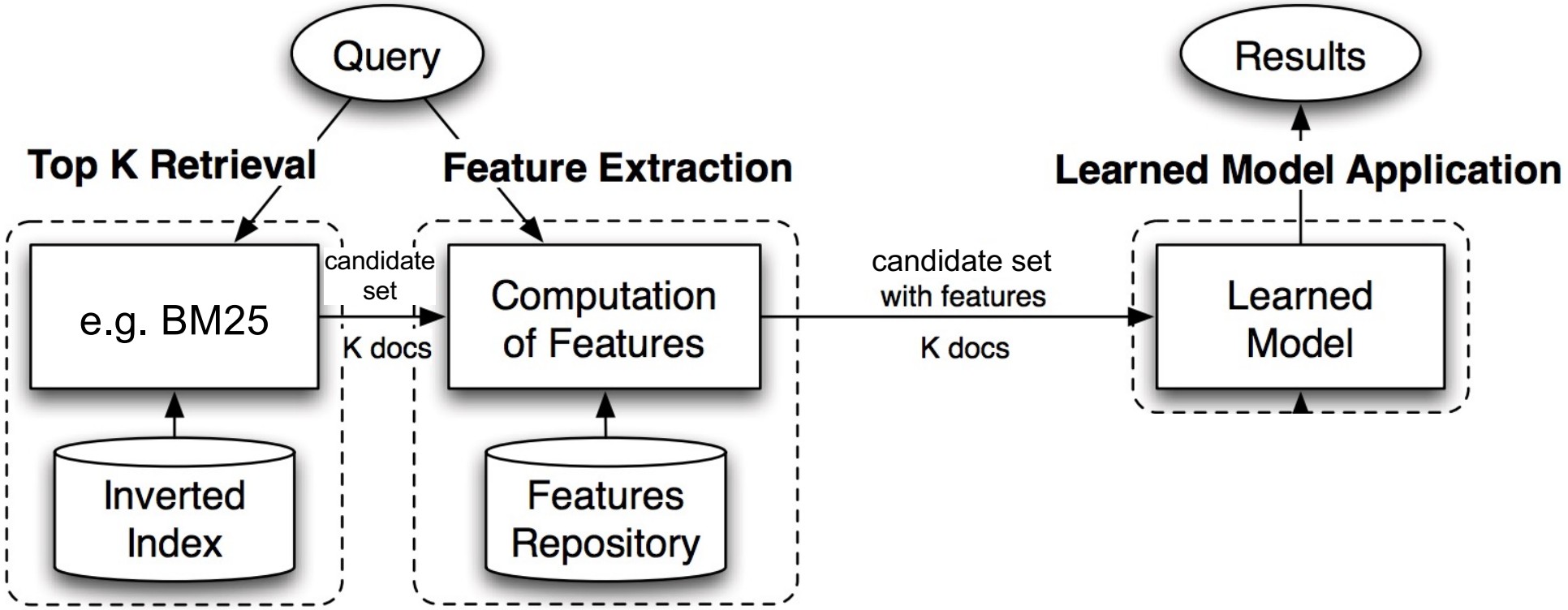
R

qid	docno	score
q1	d5	(bm25 score)

R_f

qid	docno	score	features
q1	d5	(bm25 score)	[tf score, pl2 score]

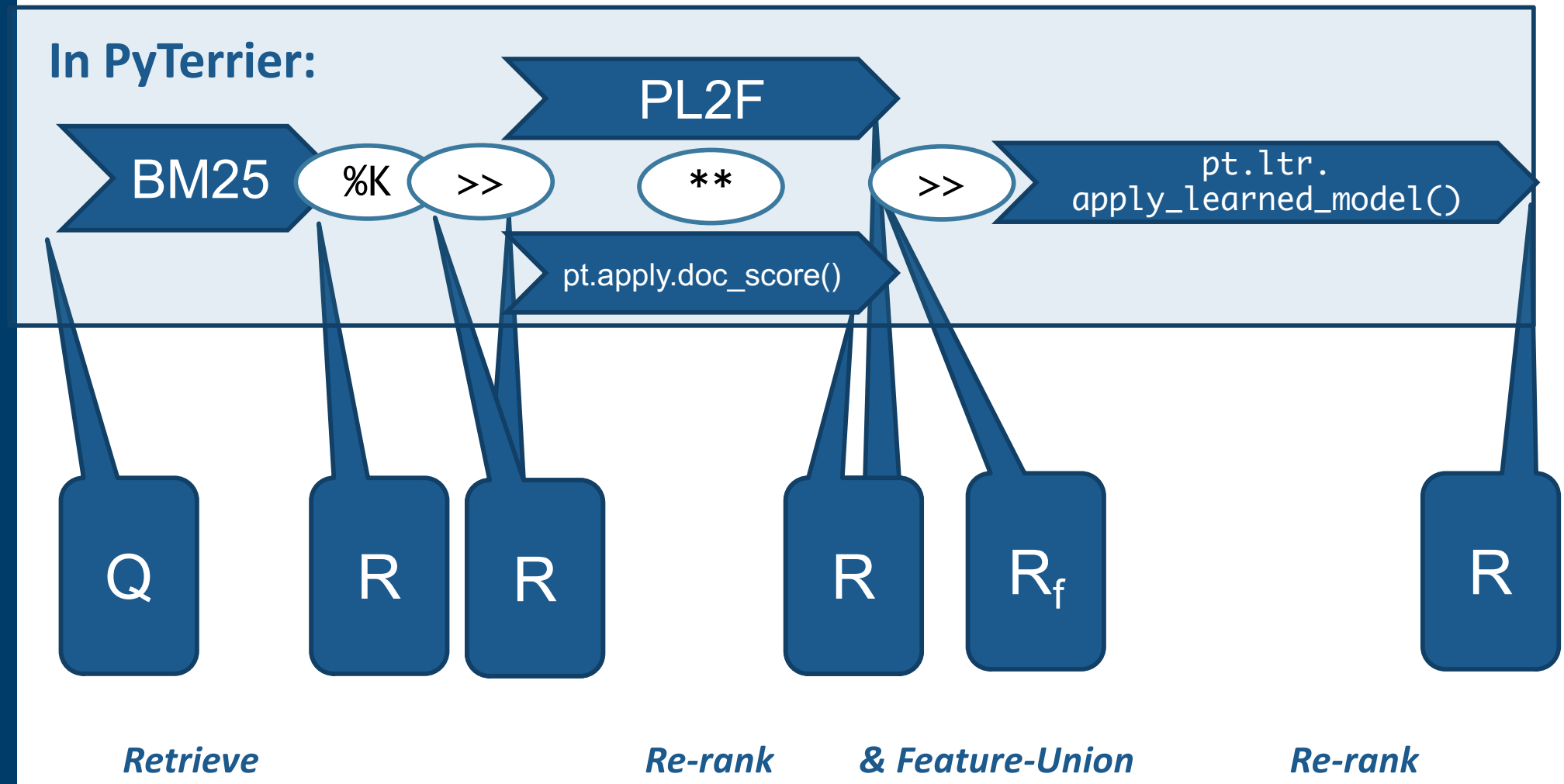
Matching LTR concepts to PyTerrier…



In PyTerrier:

BM25 %K >> PL2F ** pt.apply.doc_score() >> pt.ltr.apply_learned_model()

Data Model Transformations



Query-Dependent Feature Extraction

```
BatchRetrieve("BM25")  >>  ( BatchRetrieve("Tf") ** BatchRetrieve("PL2") )
```

Here we are using BatchRetrieve as a re-ranker

- Feature union is only defined on an input set of documents
- RHS BatchRetrieves will re-score the BM25 retrieved documents using the other weighting models

We might deploy a number of query dependent features

- Such as additional weighting models, e.g. fields/proximity, that are calculated based on information in the inverted index
- Each BatchRetrieve causes another access to the inverted index posting lists

FeatureBatchRetrieve is an alternative for Terrier

```
pt.FeatureBatchRetrieve(index, wmodel="BM25",
        features=["WMODEL:Tf", "WMODEL:PL2"])
```

- Multiple features scored in a single pass of the inverted index
- PyTerrier can perform this optimisation when `.compile()` is called

C Macdonald et al. (2012). About Learning Models with Multiple Query Dependent Features. TOIS 31(3).

TYPES OF MODELS FOR LTR

Types of Learned Models (1) Linear Model

Linear Models (the most intuitive to comprehend)

- Many learning to rank techniques generate a linear combination of feature values:

$$score(d,Q) = \sum_f w_f \cdot value_f(d)$$

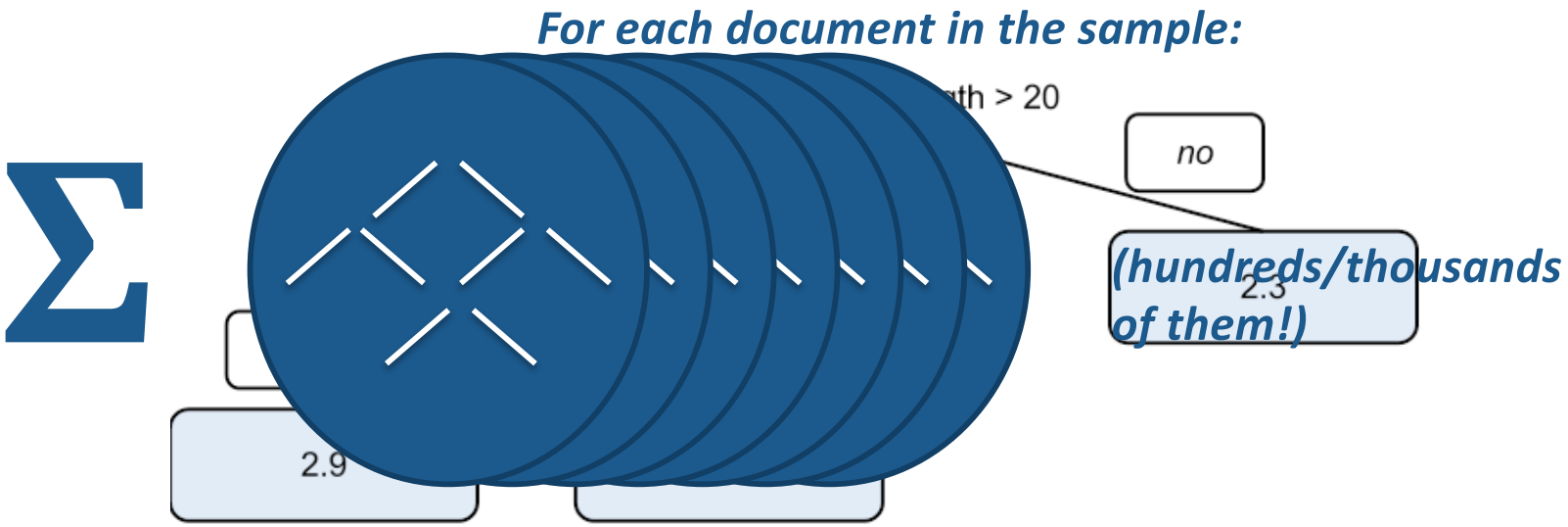
- Linear Models make some assumptions:
  - ***Feature Usage***: They assume that the same features are needed by all queries
  - ***Model Form***: The model is only a linear combination of feature values.
    - Contrast this with genetic algorithms, which can learn functional combinations of features, by randomly introducing operators (e.g. try divide feature *a* by feature *b*), but are unpractical to learn

It is difficult to find w_f values that maximise the performance of an IR evaluation metric, as they are non-smooth and non-differentiable

- Typically, techniques such as simulated annealing or stochastic gradient descent are used to empirically obtain w_f values

Type of Learned Models (2) Regression Trees

- A *regression tree* is series of decisions, leading to a partial score output
- The outcome of the learner is a "forest" of many such trees, used to calculate the final score of a document for a query
- Their ability to customise branches makes them more effective than linear models
- Regression trees are pointwise in nature, but several major search engines have created adapted regression tree techniques that are listwise
  - E.g. Microsoft's LambdaMART is at the heart of the Bing search engine



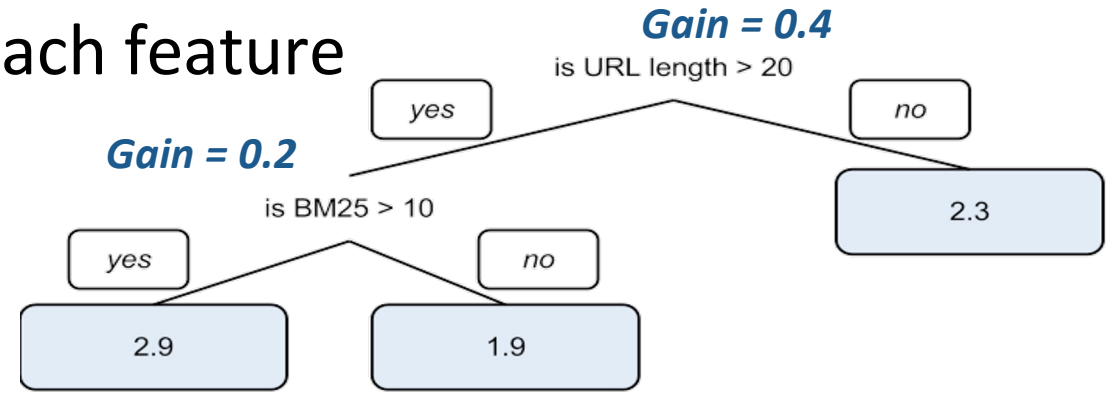
S. Tyree, K. Weinberger, K. Agrawal, J. Paykin. (2011). Parallel Boosted Regression Trees for Web Search Ranking. WWW'11.

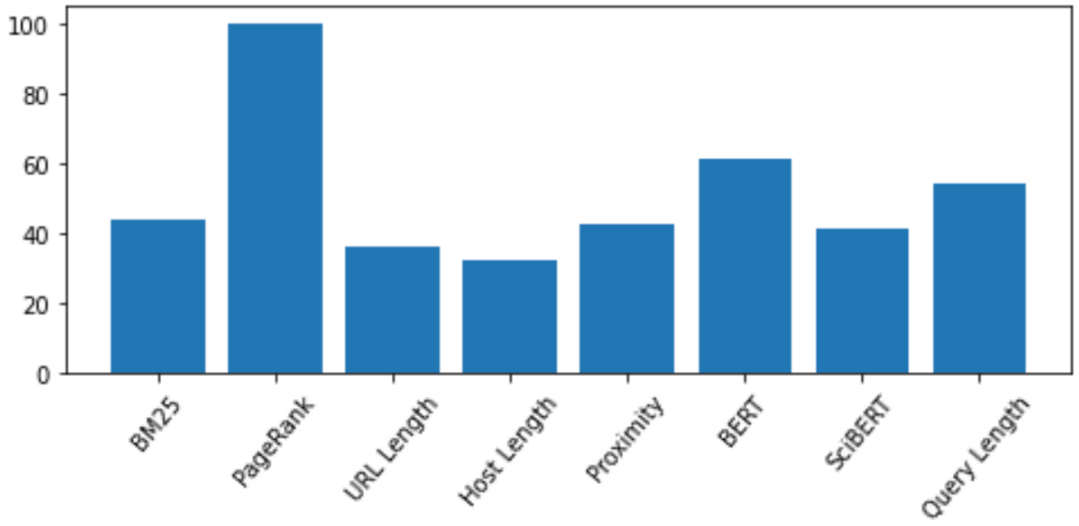
Feature Importance

Regression Trees have an in-built measure of feature importance

- By recording the "gain" at each node during training time
- Summing the gains for each feature

Feature	Norm. Total Gain
BM25	45
PageRank	100
URL Length	39
…	…





NB: sklearn's RandomForest, as well as XGBoost and LightGBM, all provide a `feature_importances_` variable

Learning and Applying a Learned Model

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PyTerrier has transformers that accept standard learners

- Accessed via `pt.ltr.apply_learned_model()`
- E.g. sci-kit learn has a random forest (pointwise) learner

```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(n_estimators=400)
rf_pipe = pipeline >> pt.ltr.apply_learned_model(rf)
rf_pipe.fit(train_topics, qrels)
```

- Also for XGBoost and LightGBM, which have LambdaMART (listwise) implementations

```
import xgboost as xgb
Lmart = xgb.sklearn.XGBRanker(objective='rank:ndcg')
lmart_pipe = pipeline >> pt.ltr.apply_learned_model(lmart_x, form="ltr")
lmart_pipe.fit(train_topics, train_qrels,
               validation_topics, validation_qrels)
```

- And for FastRank, which has coordinate ascent (linear, listwise) and random forest (pointwise) learners

https://pyterrier.readthedocs.io/en/latest/ltr.html

The Importance of Candidate Set Size

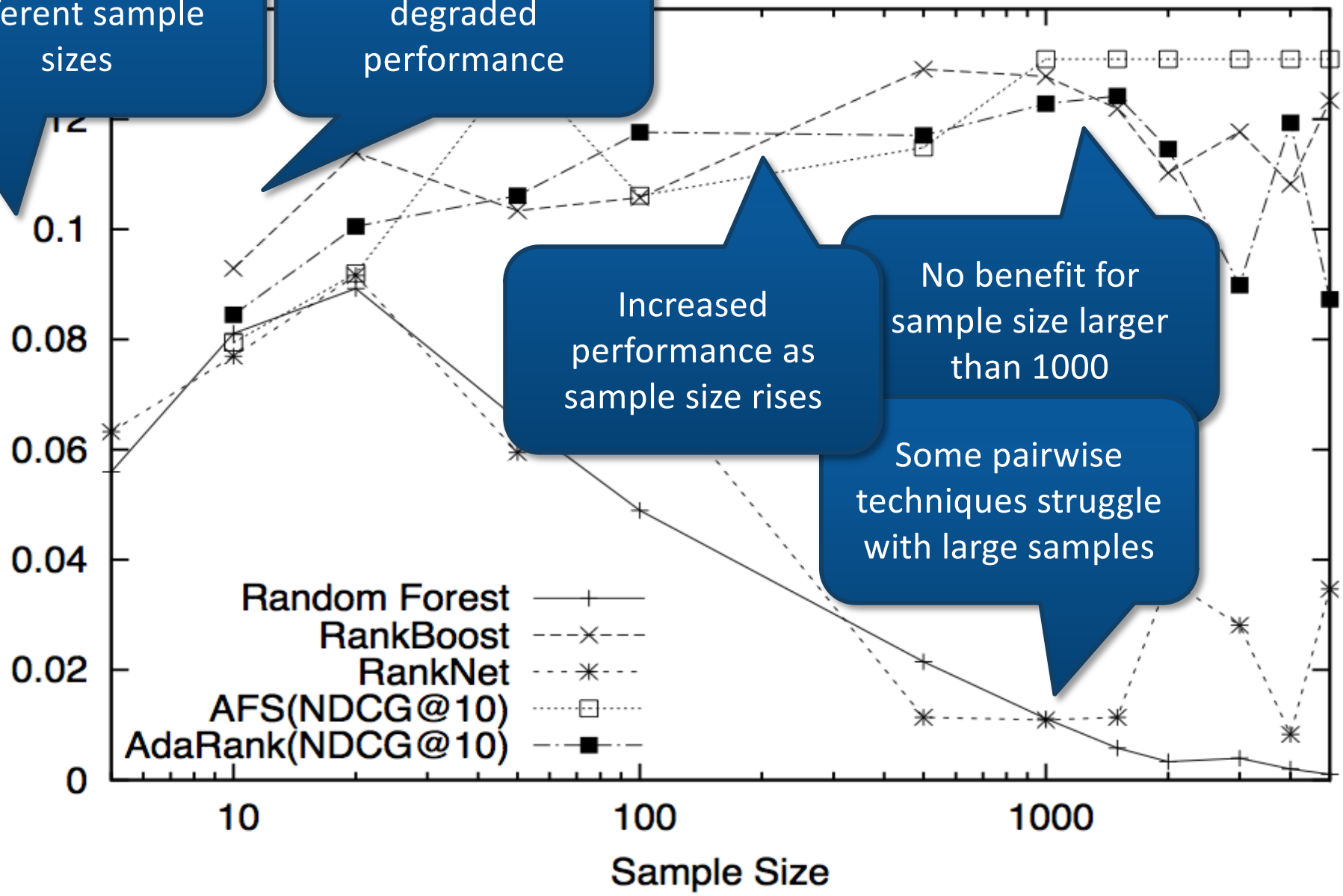
NDCG@20 for different sample sizes

Small sample size, degraded performance

Increased performance as sample size rises

No benefit for sample size larger than 1000

Some pairwise techniques struggle with large samples



C. Macdonald, R. Santos and I. Ounis. (2012). The Whens and Hows of Learning to Rank. IR Journal. DOI: 1007/s10791-012-9209-9

Analysing a Model

Many tree-based learners provide a `feature_importances_` variable

- This allows the researcher to see the importance of various features during *training*
- (How much each feature was used to reduce the loss during tree construction)

Alternatively, utility on the *test* set can be measured by ranking by each feature alone, or ablating (removing) a feature before learning

- E.g. `pt.ltr.ablate_features(int)` is a transformer that zeros out one or more features.
- This is useful when your pipeline is already defined.

```
# learn a model for 3 features, removing one each time
for fid in range(numf):
    ablated = pipeline >> pt.ltr.ablate_features(fid) >> pt.ltr.apply_learned_model(RandomForestRegressor(n_estimators=400))
    ablated.fit(trainTopics, trainQrels, validTopics, validQrels)
    rankers.append(full)
```

- You will see another analysis in the Part 2 notebook

PyTerrier Learning to Rank Summary

Key Operators: `>>`, `**`

Key Transformers:

- Retrieval: `pt.BatchRetrieve`
- Features: `pt.apply.doc_score()`, `pt.FeaturesBatchRetrieve`, `pt.BatchRetrieve`
- Learning to Rank: `pt.ltr.apply_learned_model()`
- Analyse: `pt.ltr.ablate_features()`, `pt.ltr.feature_to_score()`

LTR Integrations:

- sklearn: Regression (esp. Random Forests)
- LightGBM: Regression trees/LambdaMART
- xgBoost: Regression trees/LambdaMART
- FastRank: Coordinate Ascent (linear), Random Forests

https://pyterrier.readthedocs.io/en/latest/ltr.html

LTR Summary

Learning to rank is still an important method of integrating many features within a machine-learned search architecture

- Neural re-ranking models can also fit in this architecture
- Indeed, we found them to be the most important feature for LTR models learned on MSMARCO

PyTerrier aims to make it as easy as possible to express new features, and analyse the generated models

- We include integrations of various LTR libraries
- Tensorflow Ranking is one notable possible future integration, which blurs the lines between LTR and neural re-ranking

References

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Part 2D

WRAPUP

Achievements in Parts 1(b)

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We have reviewed modern IR architectures, namely…

- …how existing IR techniques fit into the PyTerrier datamodel and transformers
- …how transformer pipelines can be created using operators
- the learning-to-rank architecture, as well as common learners, and how to easily create features using LTR

In the practical session, you will have a chance to experience these techniques in practice on TREC Covid test collection.

In Part 2, we will review contemporary IR re-ranking architectures based on neural networks, as well allowing you to experience these through PyTerrier

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QUESTIONS?

Practical Time

The tutorial Github repo has links to the notebook for Part 2

- https://github.com/terrier-org/searchsolutions2022-tutorial
- Press the 

link for each notebook to start a Colab session

Timings:

- Practical – in breakout rooms – until 1230
- Lunch break 1230-1330
- Part 3 resumes at 1330