Feature Hashing for Scalable Machine Learning

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SPARK SUMMIT EAST 2017

About

- About me
  - @MLnick
  - Principal Engineer at IBM working on machine learning & Apache Spark
  - Apache Spark PMC
  - Author of *Machine Learning with Spark*

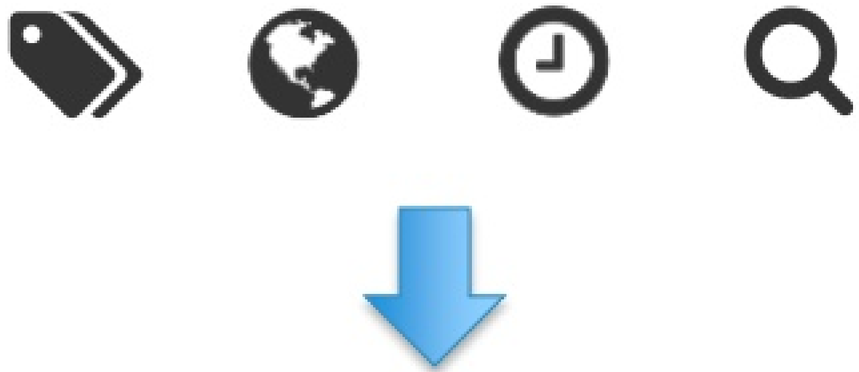
Agenda

- Intro to feature hashing
- `HashingTF` in Spark ML
- `FeatureHasher` in Spark ML
- Experiments
- Future Work

Intro to Feature Hashing

Encoding Features

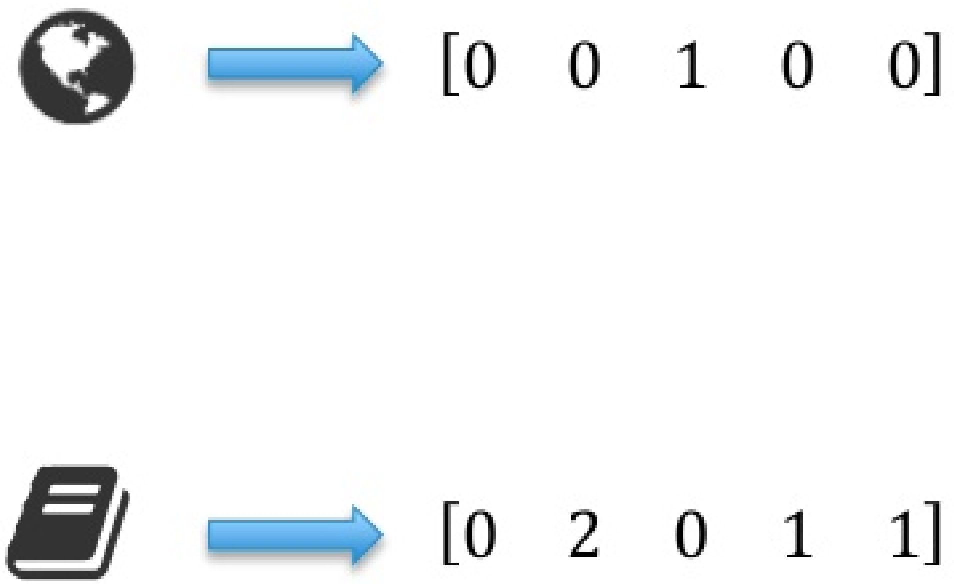
- Most ML algorithms operate on numeric feature vectors
- Features are often categorical – even numerical features (e.g. binning continuous features)



$$[2.1 \quad 3.2 \quad -0.2 \quad 0.7]$$

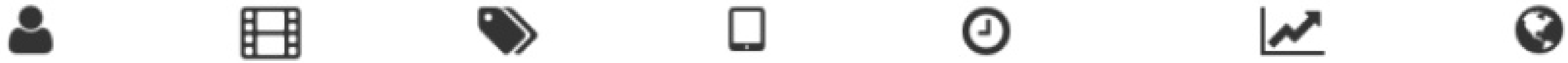
Encoding Features

- “one-hot” encoding is popular for categorical features
- “bag of words” is popular for text (or *token counts* more generally)



High Dimensional Features

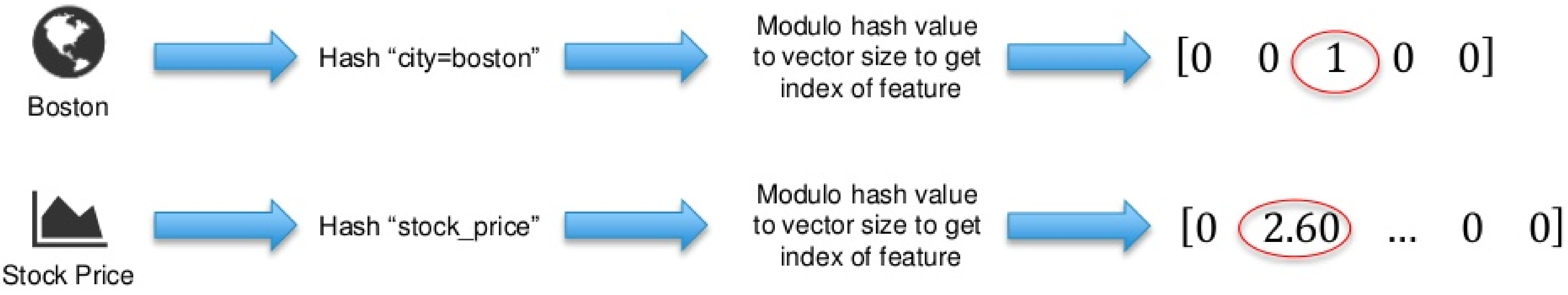
- Many domains have very high *dense* feature dimension (e.g. images, video)
- Here we're concerned with *sparse* feature domains, e.g. online ads, ecommerce, social networks, video sharing, text & NLP
- Model sizes can be very large even for simple models



[1,...,1,...,1,...,1,...,1,...,3.14,...1,...]

The “Hashing Trick”

- Use a *hash function* to map feature values to indices in the feature vector



Feature Hashing: Pros

- Fast & Simple
- Preserves sparsity
- Memory efficient
  - Limits feature vector size
  - No need to store mapping feature name -> index
- Online learning
- Easy handling of missing data
- Feature engineering

Feature Hashing: Cons

- No inverse mapping => cannot go from feature indices back to feature names
  - Interpretability & feature importances
  - But similar issues with other dim reduction techniques (e.g. random projections, PCA, SVD)
- Hash collisions …
  - Impact on accuracy of feature collisions
  - Can use signed hash functions to alleviate part of it

HashingTF in Spark ML

HashingTF Transformer

- Transforms text (sentences) -> term frequency vectors (aka “bag of words”)
- Uses the “hashing trick” to compute the feature indices
- Feature value is term frequency (*token count*)
- Optional parameter to only return binary *token occurrence* vector

HashingTF Transformer

```
val tokenizer = new Tokenizer().setInputCol("text").setOutputCol("terms")
val hashingTf = new HashingTF().setInputCol("terms").setOutputCol("features")
val pipeline = new Pipeline().setStages(Array(tokenizer, hashingTf))
val model = pipeline.fit(df)
```

```
+-------------------+-------------------------+-------------------------------------------------------+
|text               |terms                    |features                                               |
+-------------------+-------------------------+-------------------------------------------------------+
|The quick brown fox|[the, quick, brown, fox]|(262144,[22323,38208,103838,129637],[1.0,1.0,1.0,1.0])|
|jumps over         |[jumps, over]            |(262144,[179832,252565],[1.0,1.0])                     |
|the lazy dog       |[the, lazy, dog]         |(262144,[51504,75919,103838],[1.0,1.0,1.0])            |
+-------------------+-------------------------+-------------------------------------------------------+
```

Hacking HashingTF

```
val stringsDF = df.select(inputCols: _*).rdd.map { case row =>
        val seq = inputCols.map { colName =>
                val value = row.getString(row.fieldIndex(colName))
                s"$colName=$value"
        }
        (row.getInt(0), seq)
}.toDF("label", "raw")
val hashingTf = new HashingTF().setInputCol("raw").setOutputCol("features")
```

label	i1	i2	i3	i4	i5	i6	i7	i8	i9
0	1	1	5	0	1382	4	15	2	181
0	2	0	44	1	102	8	2	2	4
0	2	0	1	14	767	89	4	2	245
0	NULL	893	NULL	NULL	4392	NULL	0	0	0
0	3	-1	NULL	0	2	0	3	0	0

label	raw	features
0	[i1=1, i2=1, i3=5...	(262144,[2411,726...
0	[i1=2, i2=0, i3=4...	(262144,[5352,934...
0	[i1=2, i2=0, i3=1...	(262144,[14069,15...
0	[i1=NULL, i2=893,...	(262144,[4201,693...
0	[i1=3, i2=-1, i3=...	(262144,[6935,140...

- `HashingTF` can be used for categorical features…
- … but doesn't fit neatly into Pipelines

FeatureHasher in Spark ML

FeatureHasher

- Flexible, scalable feature encoding using *hashing trick*
- Support multiple input columns (numeric or string, i.e. categorical)
- *One-shot* feature encoder
- Core logic similar to `HashingTF`

FeatureHasher

```
def hashFeatures = udf { row: Row =>
  val map = new OpenHashMap[Int, Double]()
  $(inputCols).foreach { case field =>
    val (rawIdx, value) = if (realFields(field)) {
      val value = row.getDouble(row.fieldIndex(field))
      val hash = hashFunc(field)
      (hash, value)
    } else {
      val value = row.getString(row.fieldIndex(field))
      val fieldName = s"$field=$value"
      val hash = hashFunc(fieldName)
      (hash, 1.0)
    }
    val idx = Utils.nonNegativeMod(rawIdx, $(numFeatures))
    map.changeValue(idx, value, v => v + value)
    (idx, value)
  }
  Vectors.sparse($(numFeatures), map.toSeq)
}
```

- Operates on entire Row
- Determining feature index
  - Numeric: feature name
  - String: “feature=value”
- String encoding => effectively “one hot”

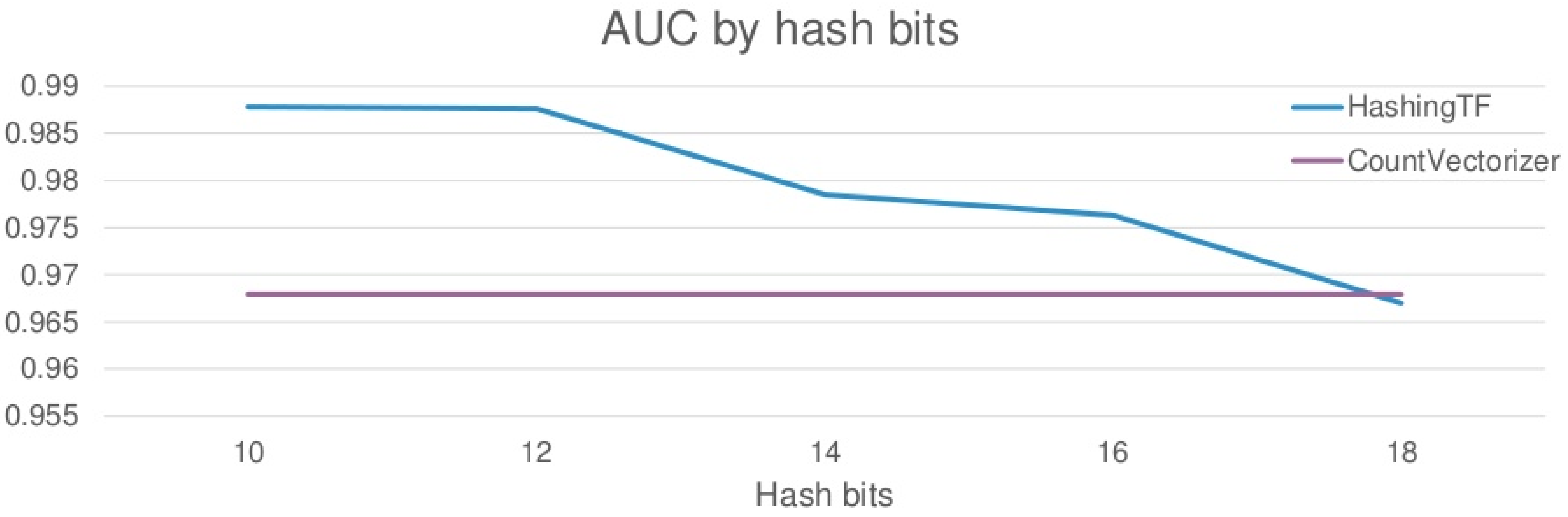
FeatureHasher

city	country	doubles	ints	hashedFeatures
Boston	US	2.5	5	(262144,[104522,110123,199626,221251],[1.0,2.5,1.0,5.0])
New York	US	3.5	2	(262144,[104522,110123,174054,221251],[1.0,3.5,1.0,2.0])
Cape Town	ZA	1.2	3	(262144,[24936,110123,166603,221251],[1.0,1.2,1.0,3.0])

Experiments

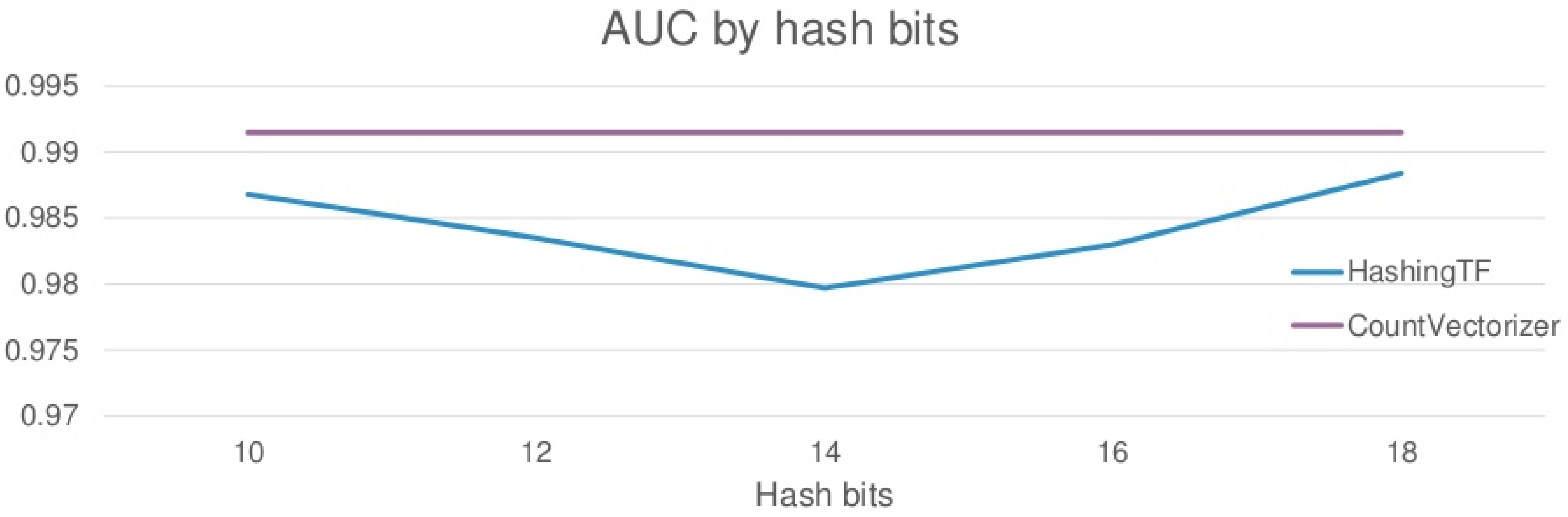
Text Classification

- Kaggle Email Spam Dataset



Text Classification

- Adding regularization (regParam=0.01)

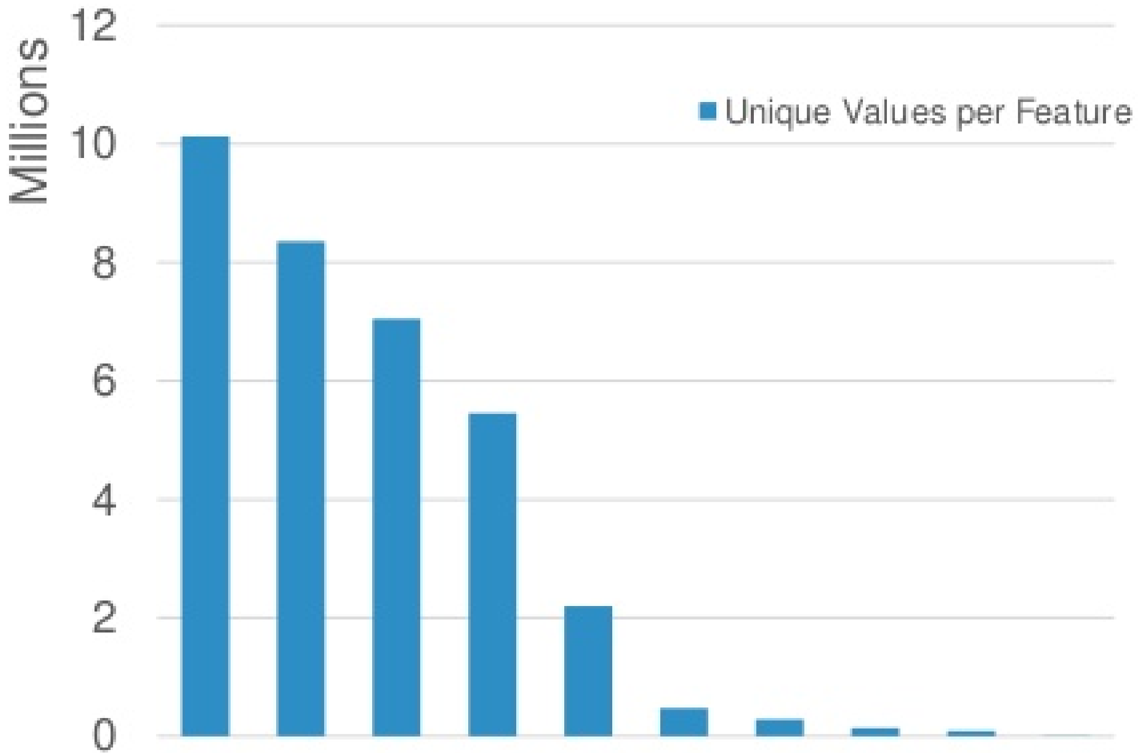


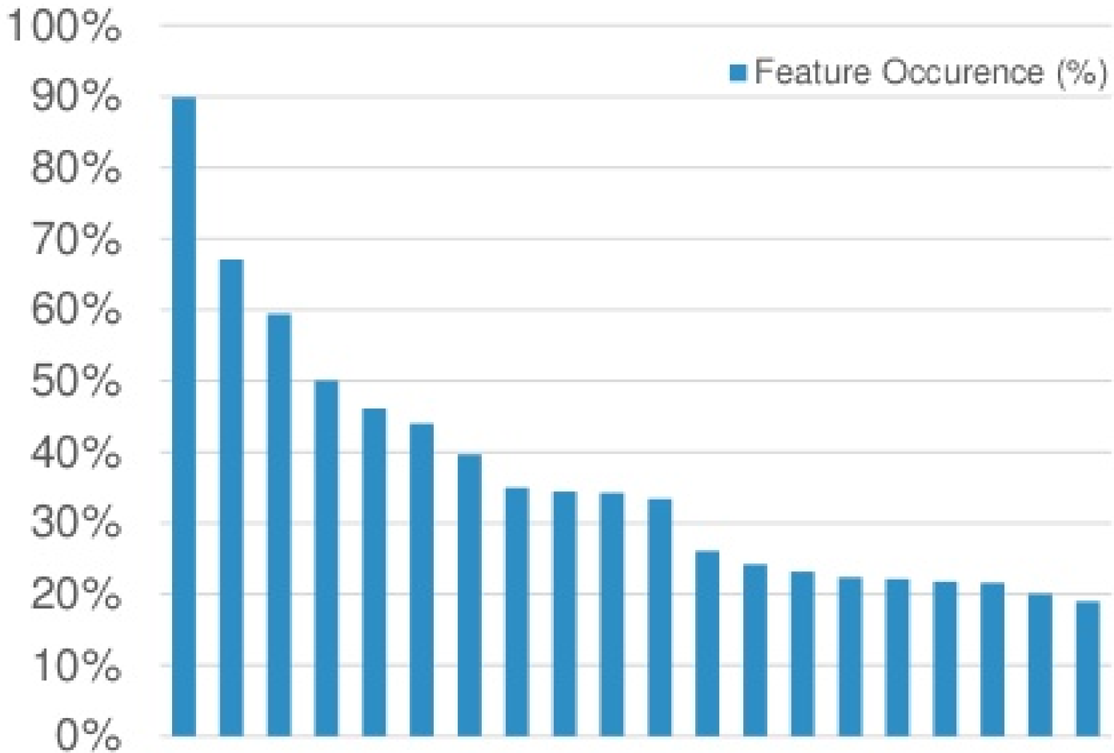
Ad Click Prediction

- Criteo Display Advertising Challenge
  - 45m examples, 34m features, 0.000003% sparsity
- Outbrain Click Prediction
  - 80m examples, 15m features, 0.000007% sparsity
- Criteo Terabyte Log Data
  - 7 day subset
  - 1.5b examples, 300m feature, 0.0000003% sparsity

Data

- Illustrative characteristics - Criteo DAC





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Challenges

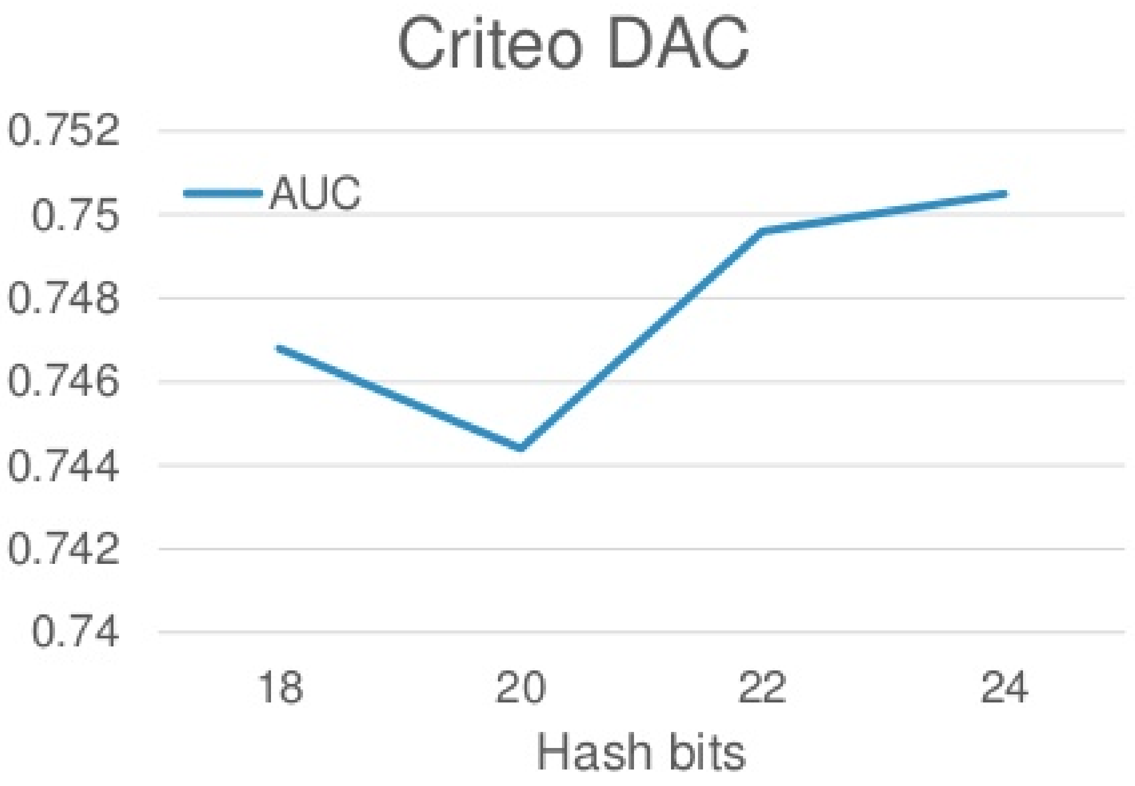
- Typical one-hot encoding pipeline failed consistently

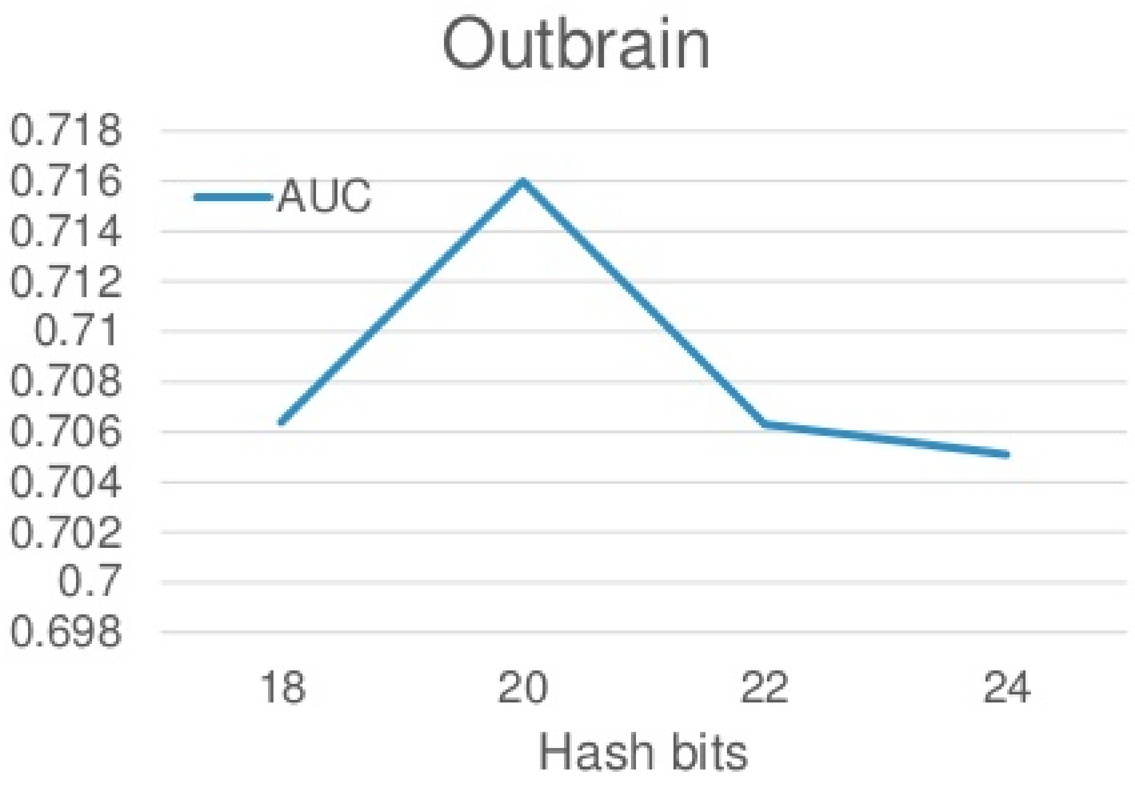
label	i1	i2	i3	i4	i5	i6	i7	i8	i9
0	1	1	5	0	1382	4	15	2	181
0	2	0	44	1	102	8	2	2	4
0	2	0	1	14	767	89	4	2	245
0	NULL	893	NULL	NULL	4392	NULL	0	0	0
0	3	-1	NULL	0	2	0	3	0	0

label	i1_idx	i1_ohe	features
0	2.0	(152,[2],[1.0])	(273492,[2,153,28...
0	3.0	(152,[3],[1.0])	(273492,[3,152,28...
0	3.0	(152,[3],[1.0])	(273492,[3,152,28...
0	0.0	(152,[0],[1.0])	(273492,[0,923,28...
0	4.0	(152,[4],[1.0])	(273492,[4,154,28...

Results

- Compare AUC for different # hash bits





Results

- Criteo 1T logs – 7 day subset
- Can train model on 1.5b examples
- 300m original features for this subset
- 2^{24} hashed features (16m)
- Impossible with current Spark ML (OOM, 2Gb broadcast limit)

Summary & Future Work

Summary

- Feature hashing is a fast, efficient, flexible tool for feature encoding
- Can scale to high-dimensional sparse data, without giving up much accuracy
- Supports multi-column "one-shot" encoding
- Avoids common issues with Spark ML Pipelines using `StringIndexer` & `OneHotEncoder` at scale

Future Directions

- Include in Spark ML
  - Watch [SPARK-13969] for details
  - Comments welcome!
- Signed hash functions
- Internal feature crossing & namespaces (ala Vowpal Wabbit)
- DictVectorizer-like transformer => one-pass feature encoder for multiple numeric & categorical columns (with inverse mapping)

References

- [Hash Kernels]
- [Feature Hashing for Large Scale Multitask Learning]
- [Vowpal Wabbit]
- [Scikit-learn]

Thank You.

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