

# A Brief History of Category Classification



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## The Price Comparison Universe

#### Shops: provide files with offers (CSV mostly)

# Offers: An article, for a price, by a shop.

#### • Products:

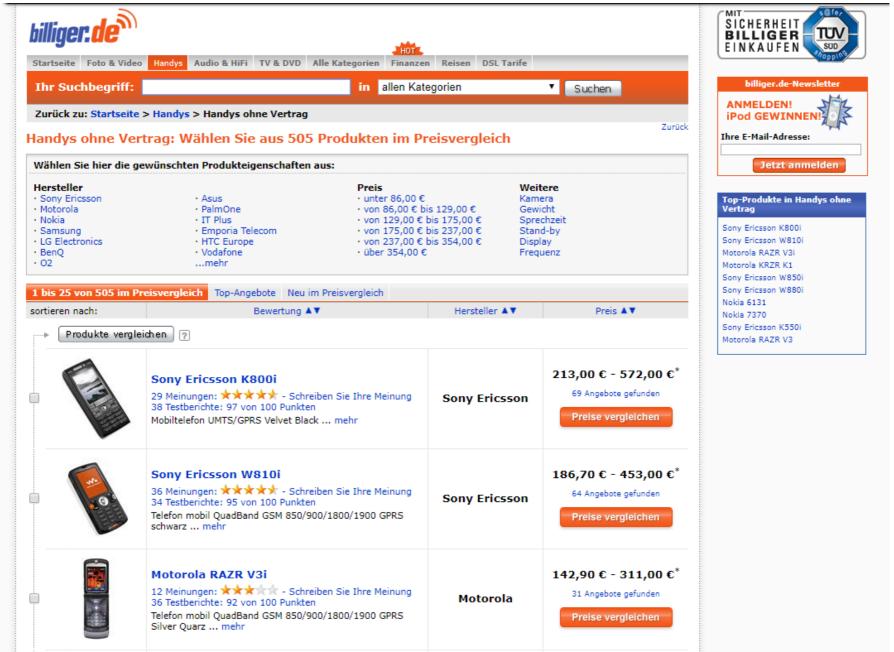
Group of offers for the same article. Created implicitly.

#### Categories:

Group of offers/products of same article type. Created explicitly.



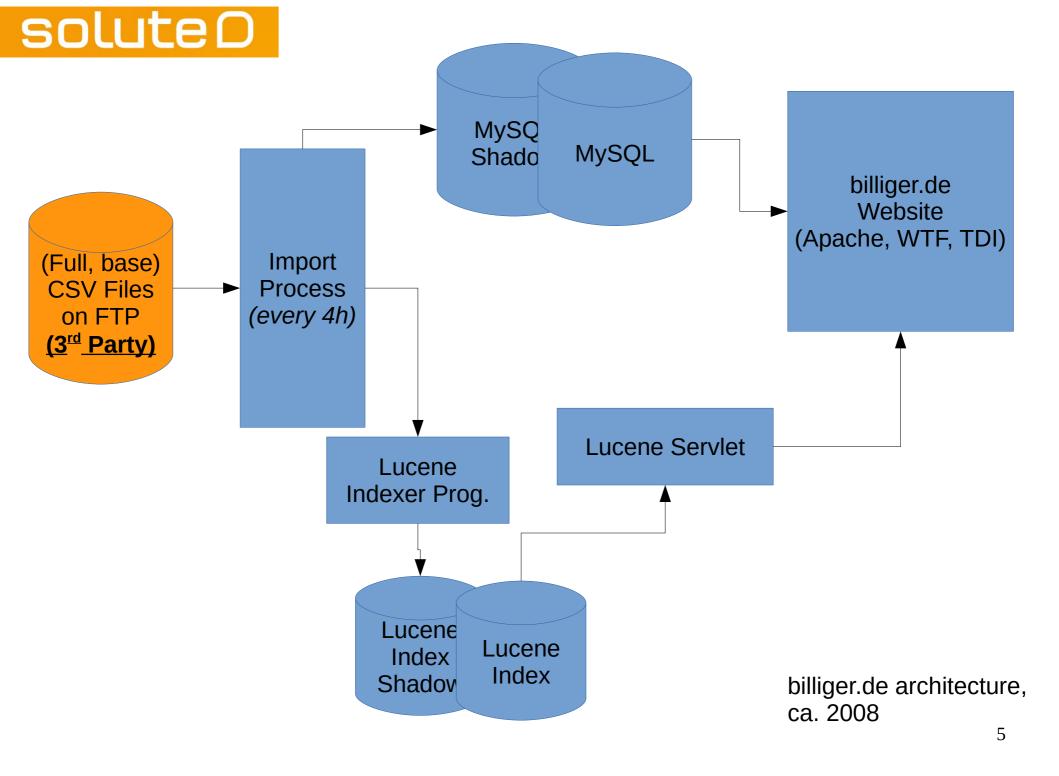
## Status Quo Ante





## Status Quo Ante

- billiger.de was just a website, no "backend"
- Exports from a third party vendor (base CSVs)
   mentasys → pangora → become → connexity
- Categorization and product matching by third party





#### Drawbacks

- Huge lag: imports only every 4h
- Errors hard to correct: no feedback API
- Expensive: revenue share with third party

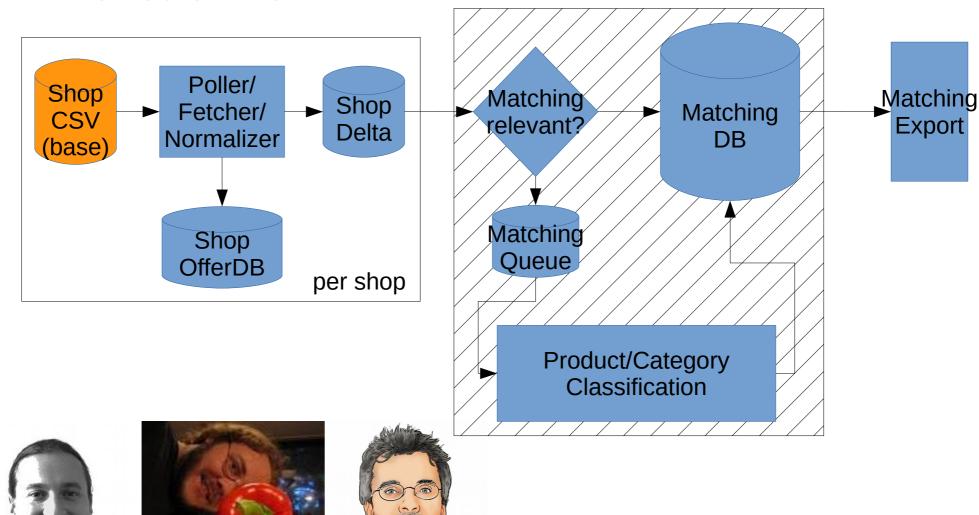


#### "EMP"

- "Eigenes Matching Projekt"
- Matching := product and category classification
- Replace the orange box...

#### "EMP"

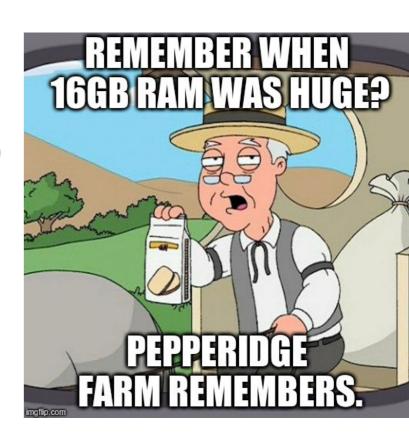
• ... a *lot* of work:



#### Classification from Scratch

#### Back then...

- 16 GB RAM was huge
- scikit-learn, NumPy not much help (yet)
- Liblinear, libsvm (C/C++)
- Training: existing offers and categories
- Our first real ML project!
- First thing you write:



#### **Precision/Recall Script!**



## First Experiments

- All data is labeled
- Experiments with simple search in labeled data (tf/idf score, allowing missing words)
  - → false positives, poor precision "Dunlop Winter Sport 205/55R16"
- Need "repellent" word scores for nearby categories!
  - → Support Vector Machine!



#### First SVM

- One model per category (one vs. many)
- Classify offer 2000×, pick highest score
- Acceptance threshold for each category
- Training based on liblinear code
- Features: just the words/tokens of the offers (cf. search ansatz)

## Infrastructure Challenges

- 2000× classification is costly → "transposed" classification: each feature brings in its possible categories (typical: few hundred)
- Holding 2000+ models in memory (for classification): strip features with low weight; watch for Python ref counting vs. COW in multiprocessing
- Building 2000+ models: C++ code, mmap(2)ed binary files, multiple processes via fork().
- Cross validation for each category (precision/recall)
- Adjusting thresholds for each category (which is worse, fp or fn?)
- LIVE!

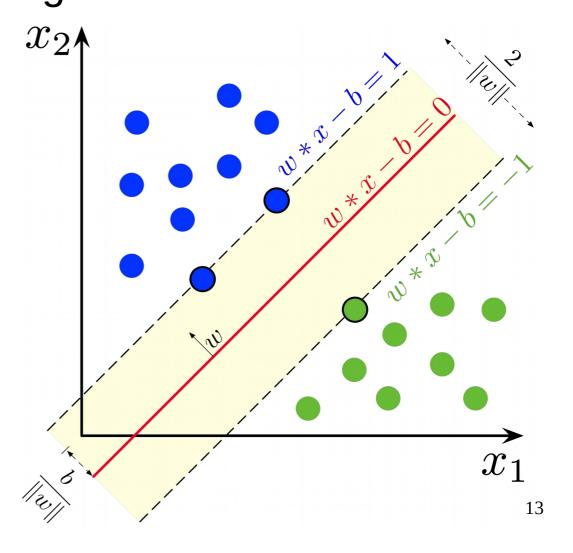


## SVM and Insights

• Hyperplane separating the points of the  $x_2$  two classes

• Score :=  $w \cdot x - b$ 

Weights mean something



## SVM Models are Intelligible

0.00323284 beautiful

0.00240695 lieferumfang<sup>14</sup>

3.66 3.59 3.44 3.28 3.18	mpaxx technimax yp 4gb techniplayer xemio	-3.24 -3.61 -3.64 -3.99 -4.87	tasche akkus cd dockir tasche zubeh	ne s ingstation nen
3.13	mpixx	-6.55	für	
3.12	2gb			MP3 Players
2.98	8gb			2012
	sansa	0.004	03229	schokobraun



# Interpreting the Model

- Positive weights → Attraction
- Negative weights → Rejection
- Near-zero weights → neutral
- Negative features indicate neighboring categories
- Category taxonomy influences models



## Example: "Erotik"

- (TÜV Certificate → no sexy stuff on billiger.de)
- Some shops also carry adult toys
- Some syndication partners wanted the E
- Research: model adult vs. non-adult
- (We actually have several distinct adult categories)

#### **Erotik Model**

5.64 erotik -4.31 oboy

5.44 vibratoren -5.31 produkte

3.55 fetish -8.33 bekleidung

3.45 sextoys

3.39 sexspielzeuge

3.13 obsessive

2.98 fetisch

2.94 dildo

2.85 dorcel

Erotik 2012

oboy, bekleidung

→ neighbors...



## (Un-) Sexiest Names

2.38 heida	-0.72 davi
2.30 Helua	-U.12 uavi

2.13 mandy -0.73 oliver

1.97 eugenie -0.75 sylvester

1.83 anetta -0.88 tom

1.63 molly -0.90 erika

1.53 vanessa -1.07 lara

1.48 anderson -1.08 lucia

1.47 nadine -1.26 max

Model vs. name list

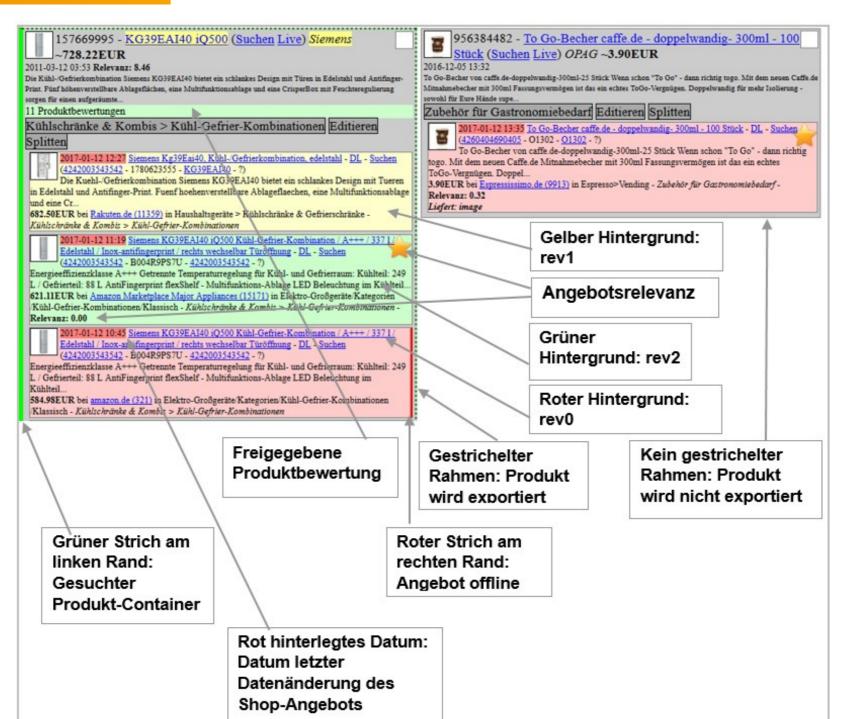
First sexy male name: Sven (pos. 17)!

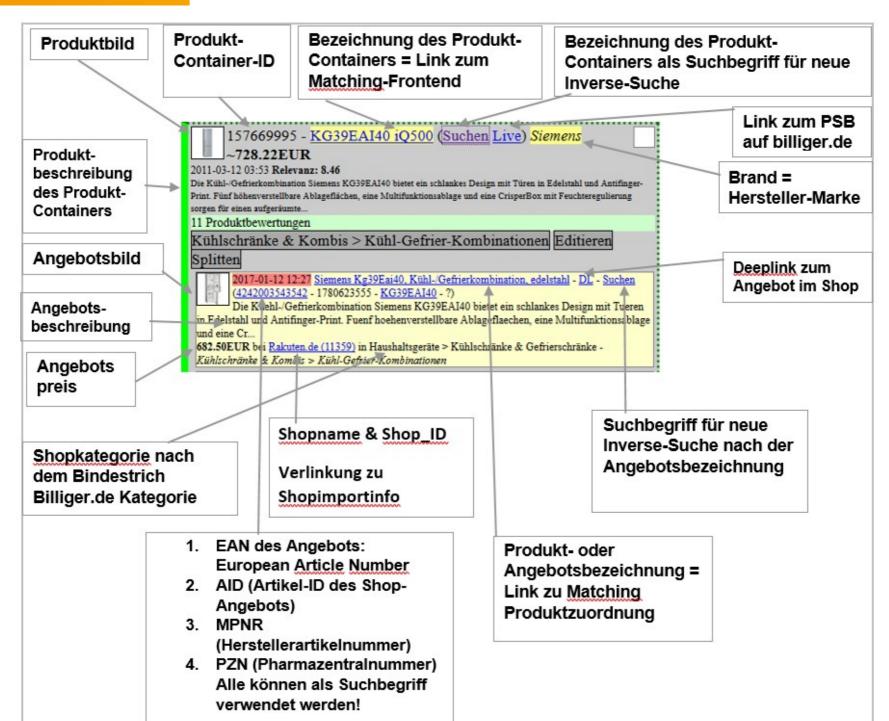
• Jenna: pos. 25, Ron: pos. 28



## Living Data

- Source of labeled data dried up
  - → need new source for training data
- New categories → need training data
- Imperfect results (also in product matching)
  - → need cleanup imMeDiAtELy!!!1elf
- InverseFE to move offers between products (and categories)
- Re-purposed cleaned up offers as training data







#### New Feature: Price

- Price as token is too sensitive: 9.99€ != 10.00€
- Token cardinality!
- Price as float still too sensitive
- Sigmoid didn't work (forgot why)
- Solution: Price Bin (0..5€, 5-10€, ...) as "token"
- Works well, often high weights

## New Feature: Shop Cat. Mk. 1

- Generate token from Shop ID and Shop Category
  - → unique shop category
- MD5 over Shop ID and Shop Cat.
- Worked well (precision and recall)...
- ... until we
  - ... got new, unlabelled shops
  - ... had categories finer than shop cats
- Generalizes poorly to new shop cats



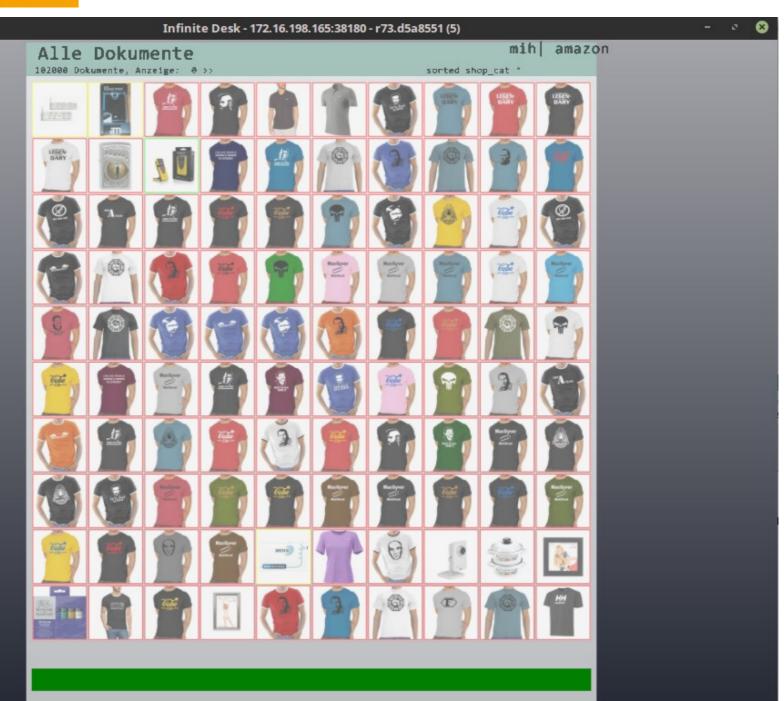
## New Feature: Shop Cat Mk. 2

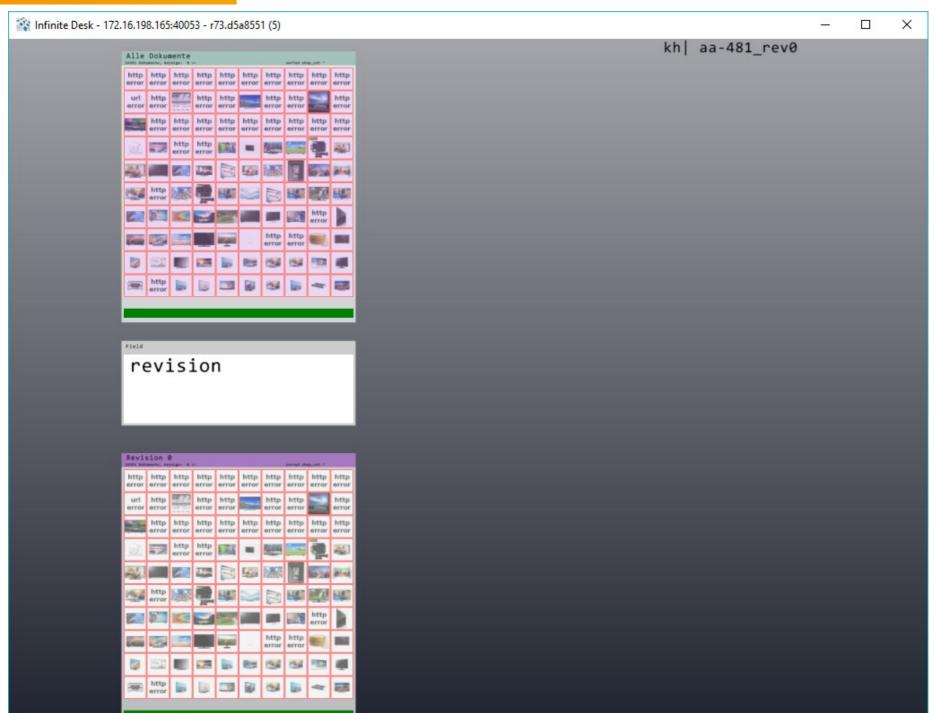
- Better generalizing solution:
- Normal tokenization
- ... with "SC\_" prefix for shop cat tokens
- No more Shop ID → generalizes over shops



## Fast Shop Cleanup

- Shops are new or complain about category classification → need tool to clean up offers of one (potentially large) shop, quick.
- Remapping Tool: cut (via search & filter) and assign category manually → labeled data.







## Growth (Pains)

- Matching DB: 20 mio offers → 200 mio offers,
   MySQL → Postgres
- Rebuilding the training binary: cur.fetchall("SELECT \*") → own map/reduce + MogileFS → Nokia Disco → Deltas
- Updating training docs → compute new + more (b/c more categories) models: parallelize over multiple machines ("mapping training service")
- Processes around Category Classification: decisions by SEO vs. taxonomy; high turnover → loss of best practices; nearshoring vs. Inverse vs. Remapping Tool



