SPARK ML WITH HIGH DIMENSIONAL LABELS

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Cadent

Cadent: Data Empowered Television Advertising

Data Technology Company specializing in Television Advertising

Cadent has built a **bicoastal** data science and engineering team

Vision

Unified Self Service Media Monetization Platform for all TV inventory

Our Team has cutting edge expertise

- Hybrid cloud Apache Spark infrastructure
- Analytical rather than rule driven algorithms
- Experience with Machine Learning APIs and custom mathematics in decision optimization

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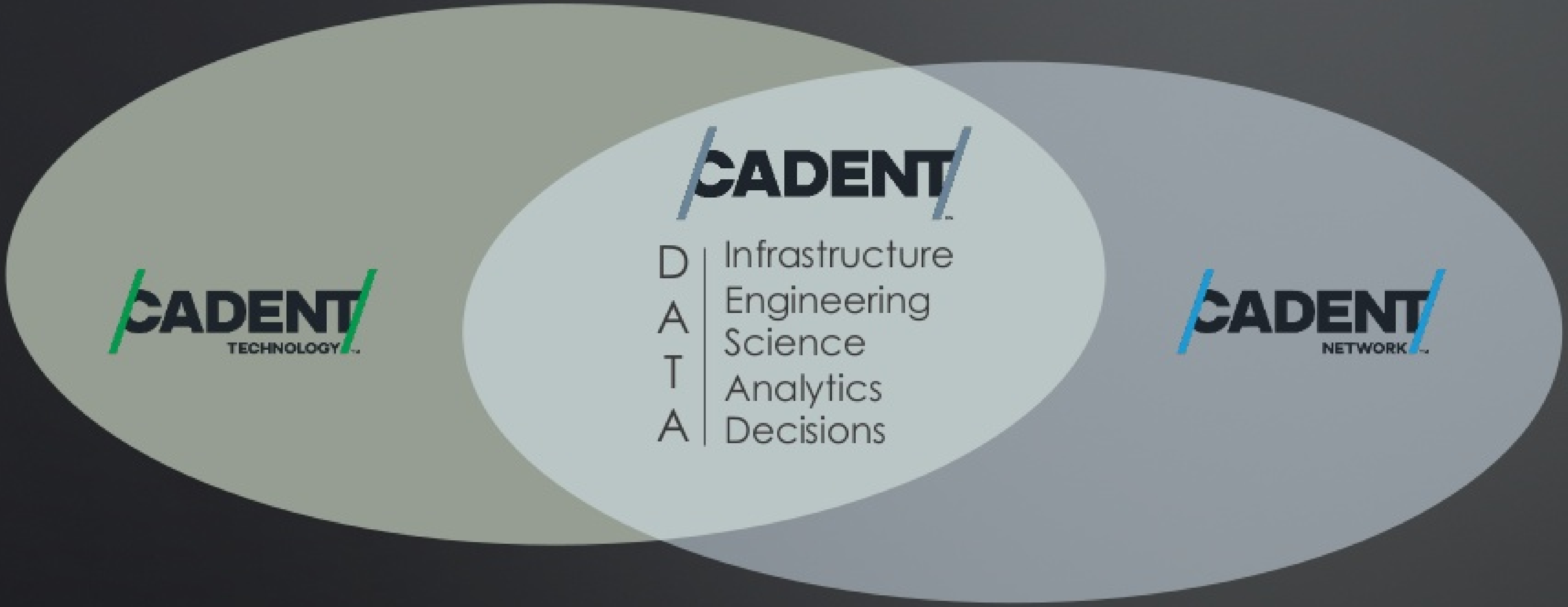
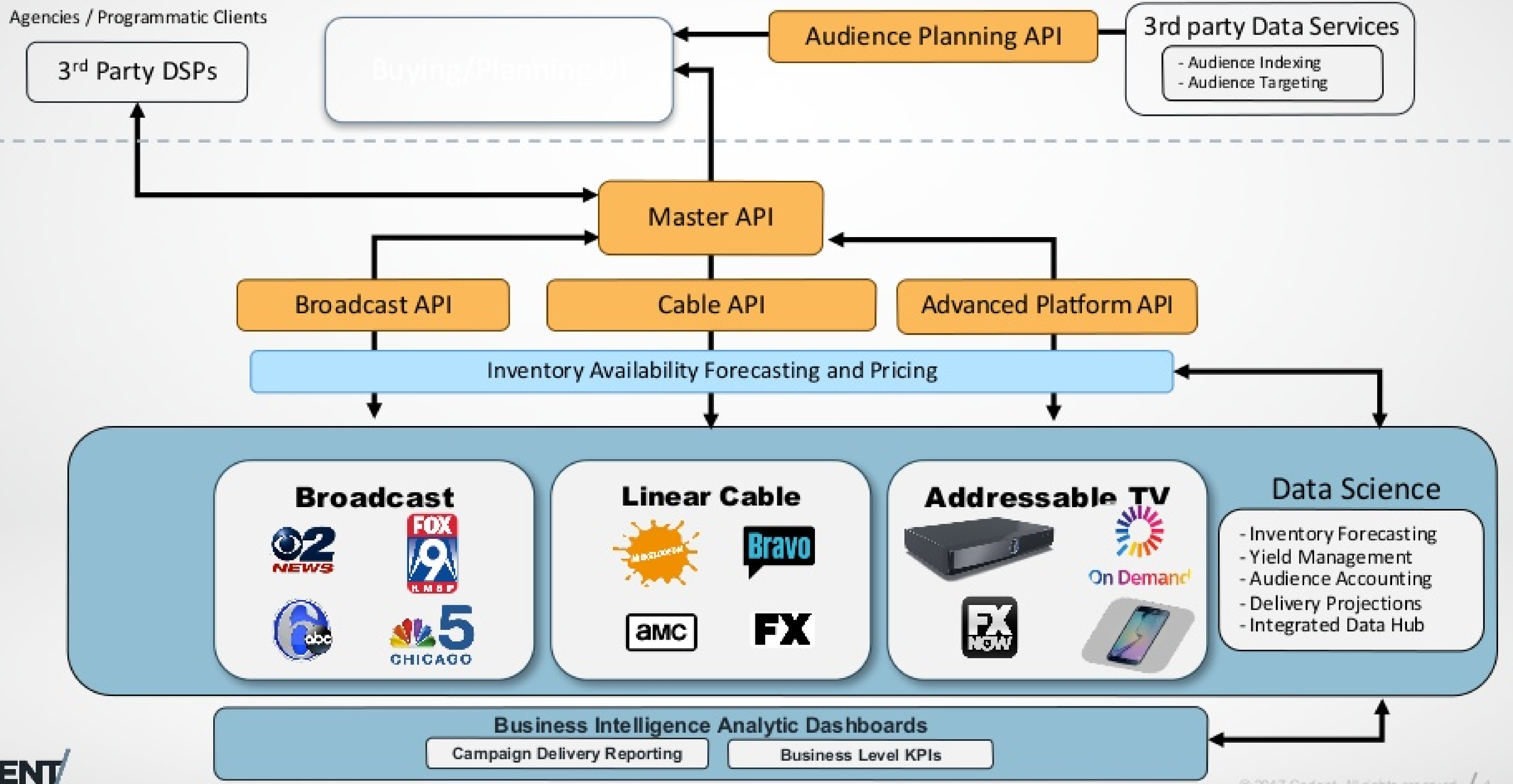


Cadent TV Buying Platform



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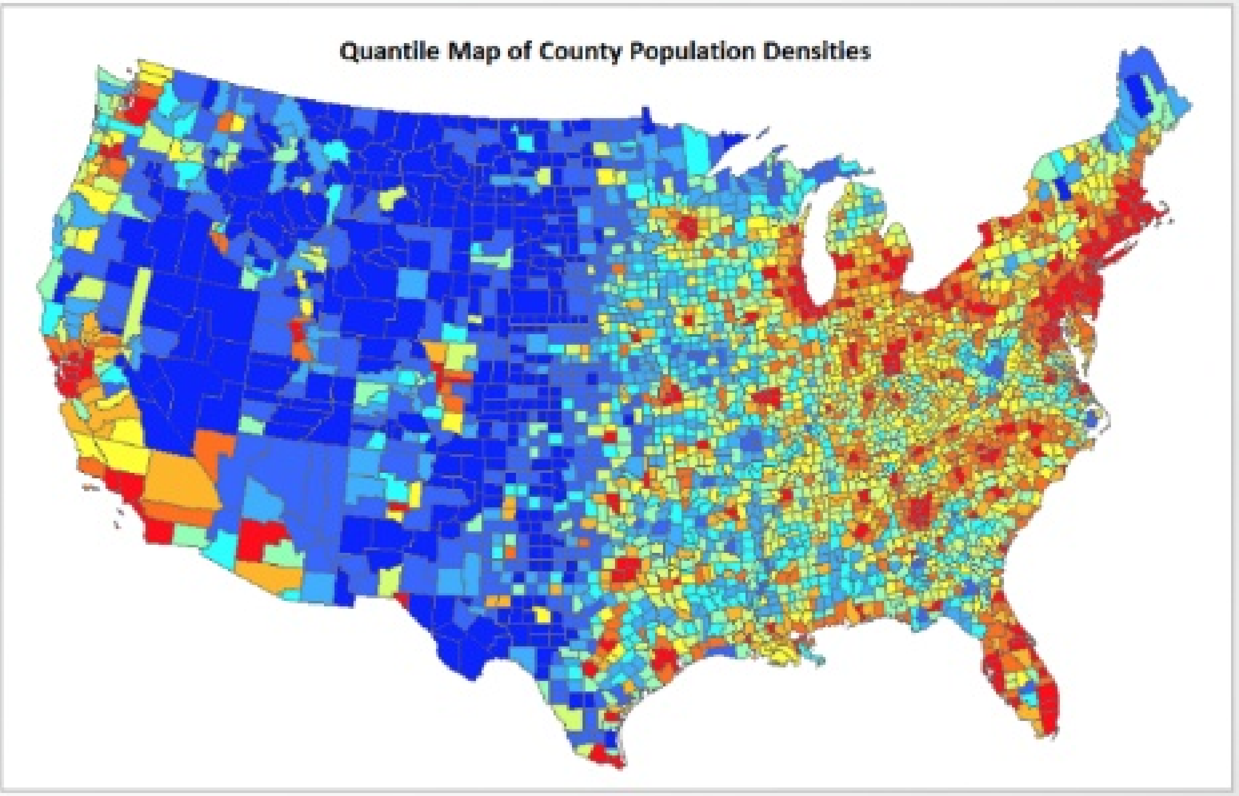
Zoom In: Local Linear Cable

- Agency
  - Buys Media to Run ads for National advertisers
- Impressions
  - “eyeballs” currency of brand advertising
- Cable Operator
  - Media Companies providing TV service
  - Loosely segregated Geographically
- Subscribers
  - Consumers of Cable Operator Services
- Ratings
  - Fraction of Subscribers tuned in
  - Not known until after the fact
  - Ill conditioned: log-scale variance
  - O(10k) dimensions: variation in Demographics, geography and television content

$$I_a = \sum_{g \in Geo} \sum_{n \in Net} \sum_{t \in time} R_{g,n,t,a} * S_{g,n,t,a}$$



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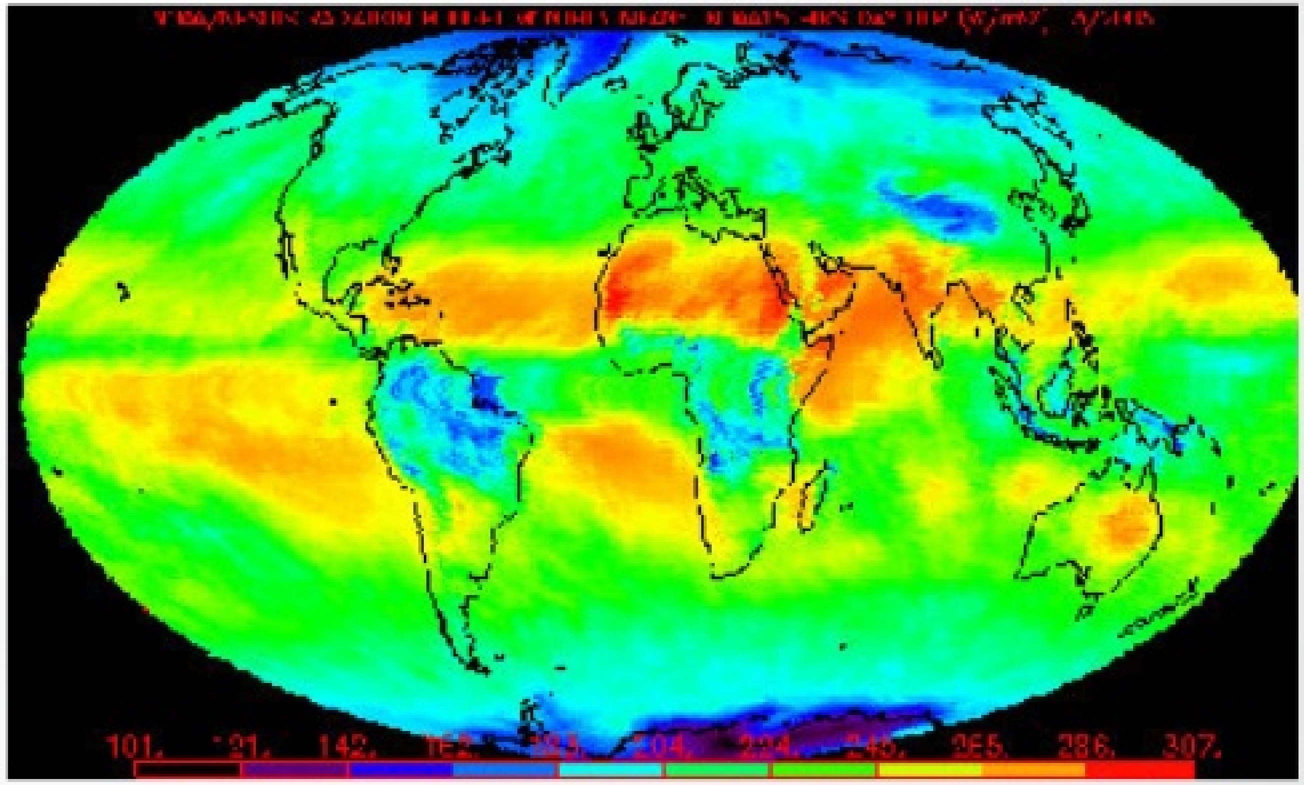
Models for Television Ratings

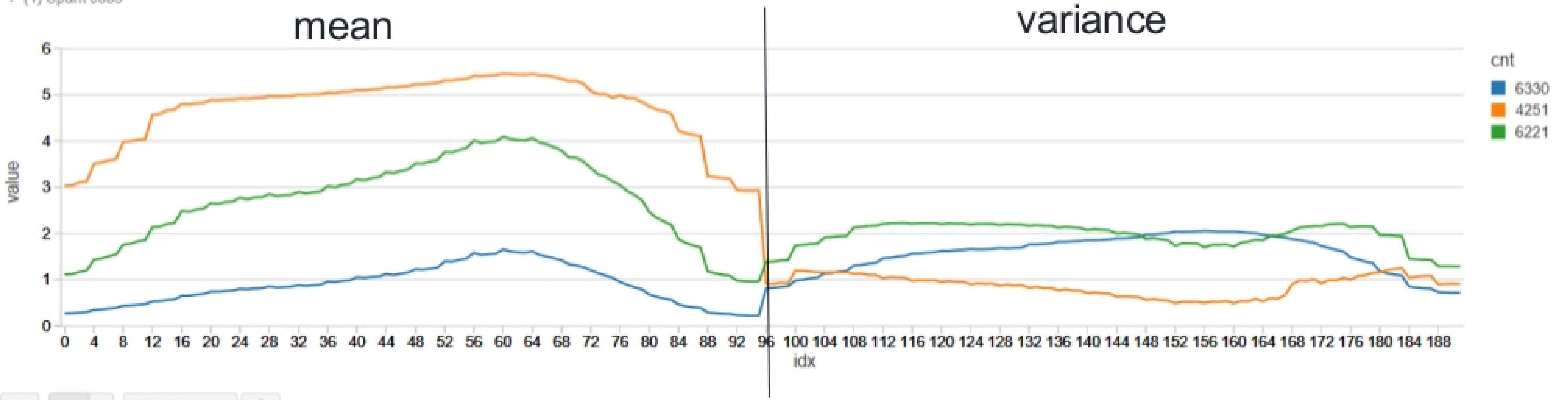
- Relevant Time Scales
  - Weather-like View
    - Shows
    - Twitter trends
    - Spectacle Events
  - Climate-like View
    - Seasonality
    - Subscriber trends
    - Daypart Variation
- Why High Dimensional?
  - In the climate view the features represent days but there significant intraday patterns
  - Pivot the daily pattern into vectors so that ML models can directly capture statistical correlations



A sense of Daily Patterns: Log Mean & Variance

```
> %sql select * from Vis_Grouping order by groupID, idx
```

▸ (1) Spark Jobs



Plot Options...

Command took 2.63 seconds -- by spanayotov@crossmw.com at 12/20/2016 11:53:27 AM on cte-spark2

Values shown in Log-like coordinate system:

value 0 = rating 0
value 3 = rating 10^(-5)
value 5 = rating 10^(-3)

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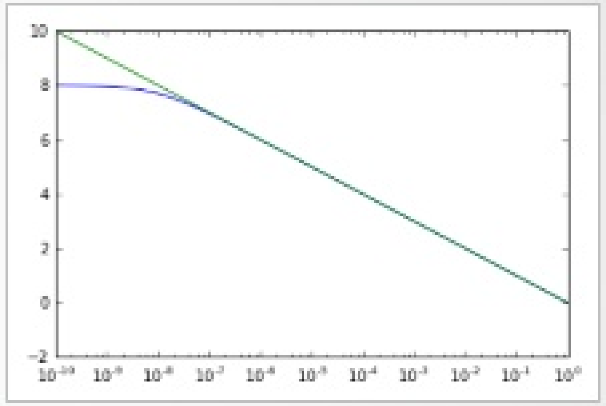
An Intuitive Coordinate System for Human Interpretation of Ratings Data

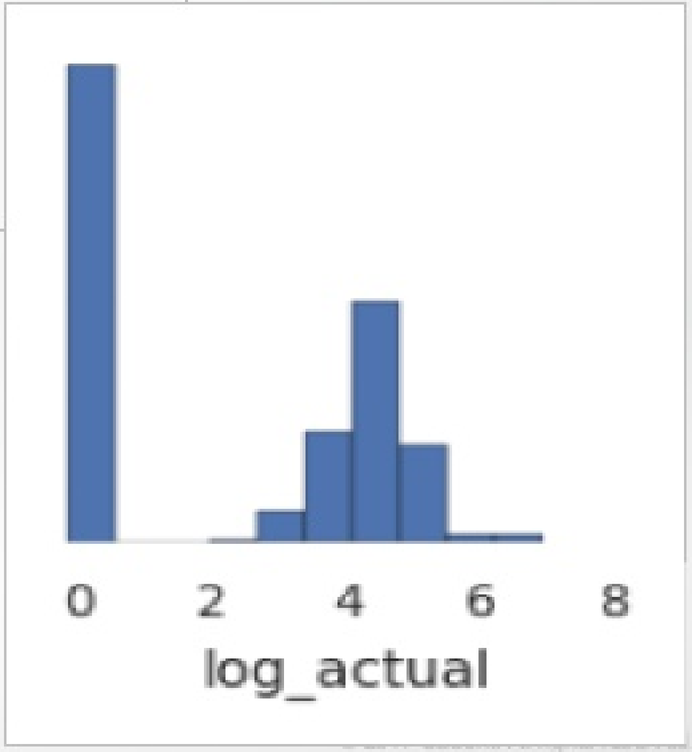
```
// *** This creates the log functions ***
def symlogGenerator(base: Double, offset: Double, flipSign: Boolean = true) = {
  val flipInt = flipSign match {case true => 1 case _ => 0}
  val sign = 1 - 2 * flipInt // value is always 1 or -1
  def logbase(lbase: Double, num: Double) = log(num)/log(lbase)
  val logOffset = - logbase(base, offset) * flipInt // log(offset, base)

  def transform(x: Double) = logOffset - sign * logbase(base, min(1,max(0,x)) + offset) // log(x + offset, base)
  def inverseTransform(y: Double) = pow(base, -(min(logOffset,max(0,y)) - logOffset) * sign) - offset

  (transform(_), inverseTransform(_))
}
// This line actually creates functions from the generator
val (t,it) = symlogGenerator(10, pow(10.0, -8.0), true)
sqlContext.udf.register("T",t)
sqlContext.udf.register("IT",it)
```



This coordinate system is used to eliminate bias in error metrics,
In the domain the errors in large value ratings swamp those of small value ratings



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DISCUSSION OUTLINE

01 THEORY

- Math

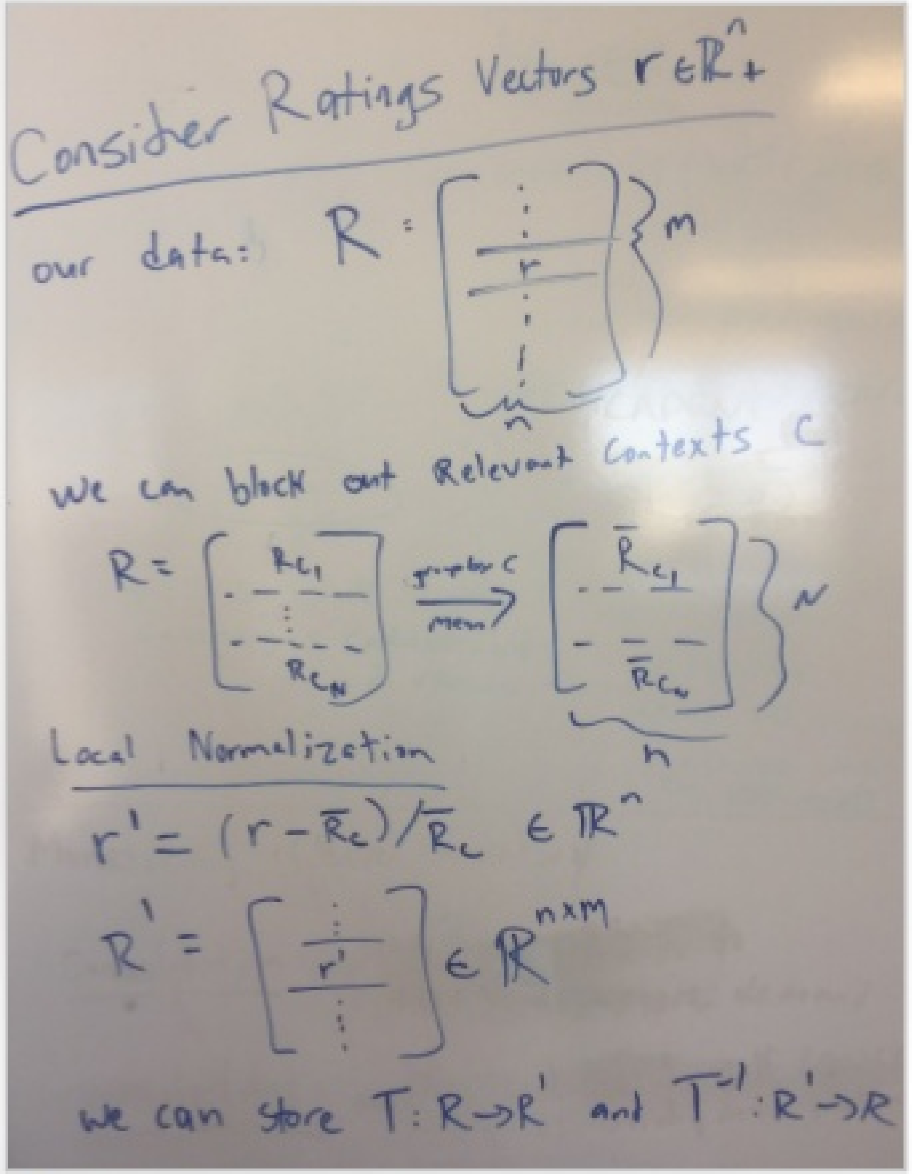
02 PRACTICE

- Code

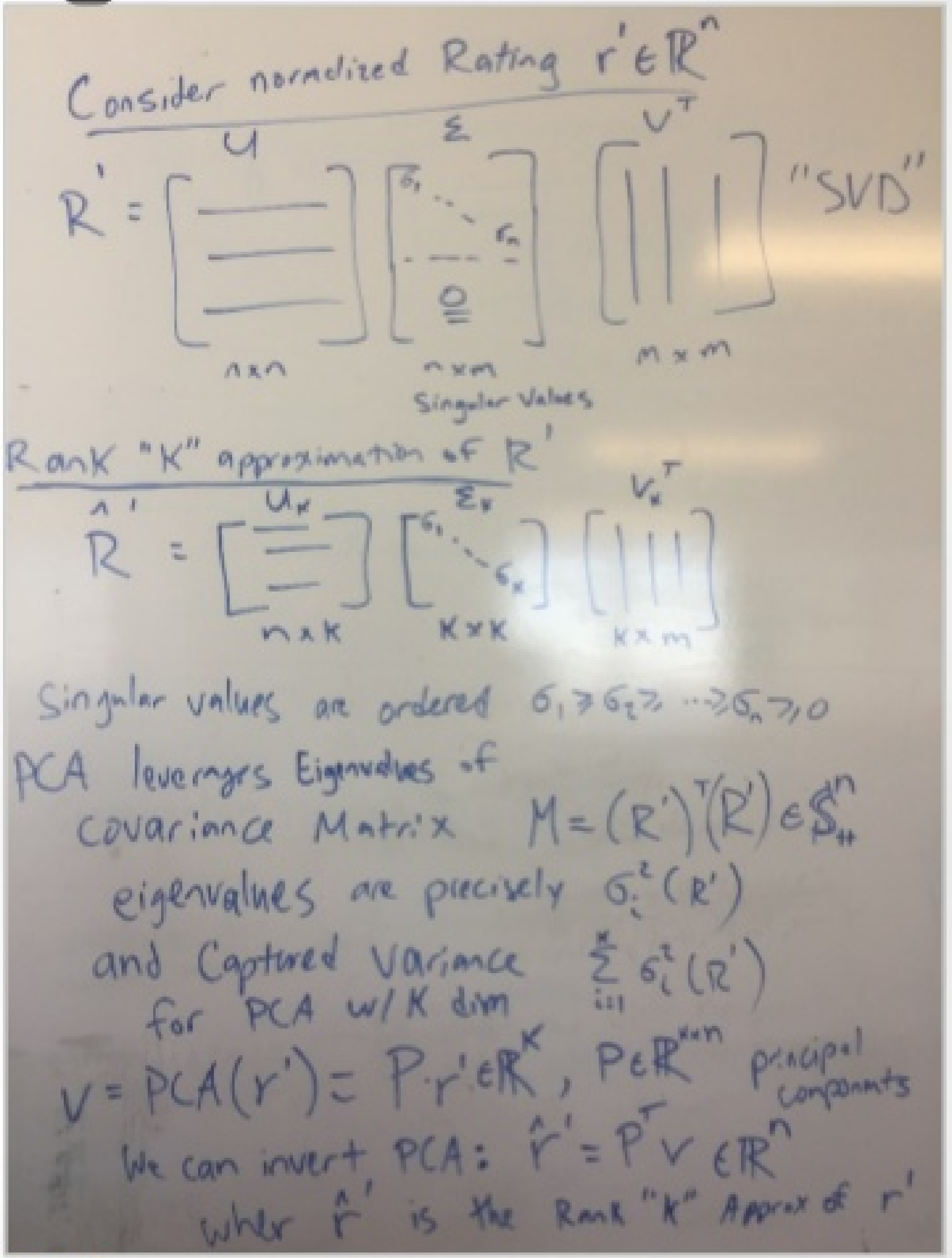
THEORY: Reframe the Problem with Math

Mathemagic… AKA Linear Algebra

Local Means as a Linear Transform

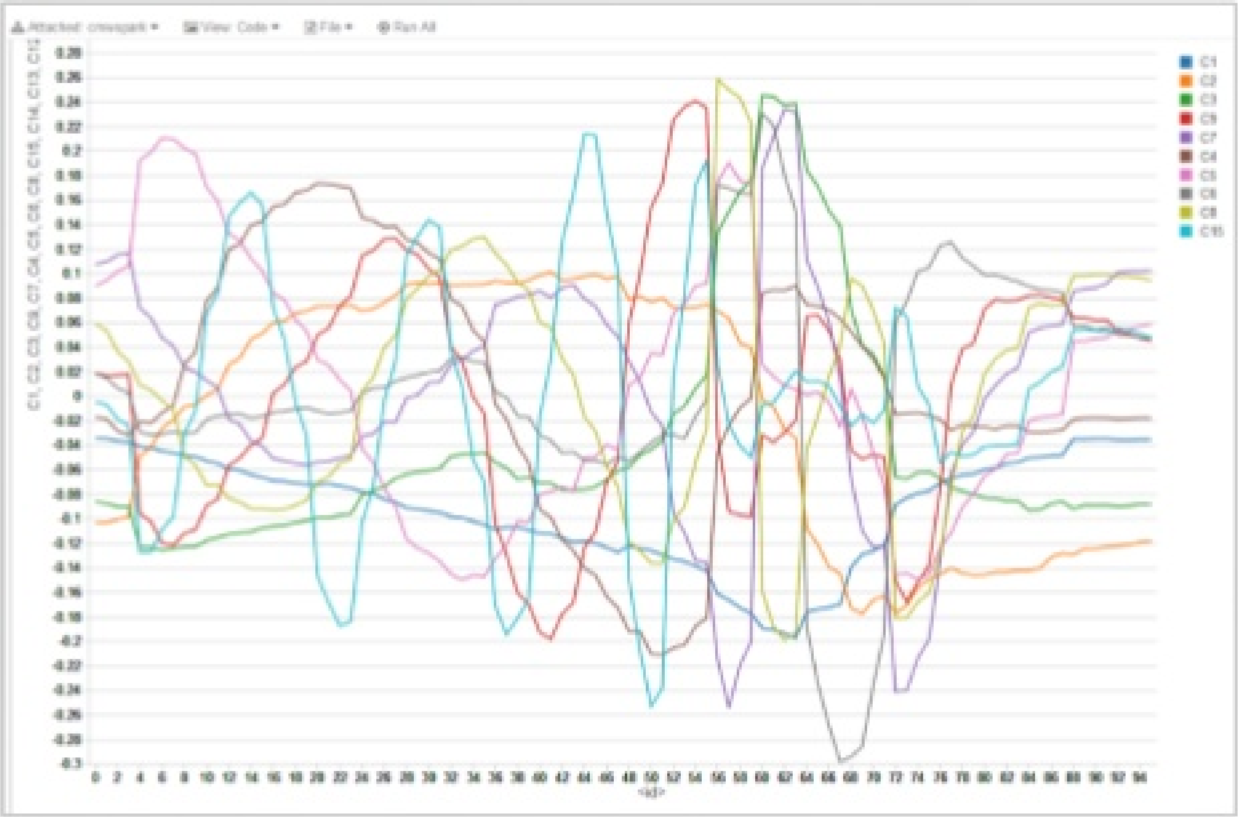


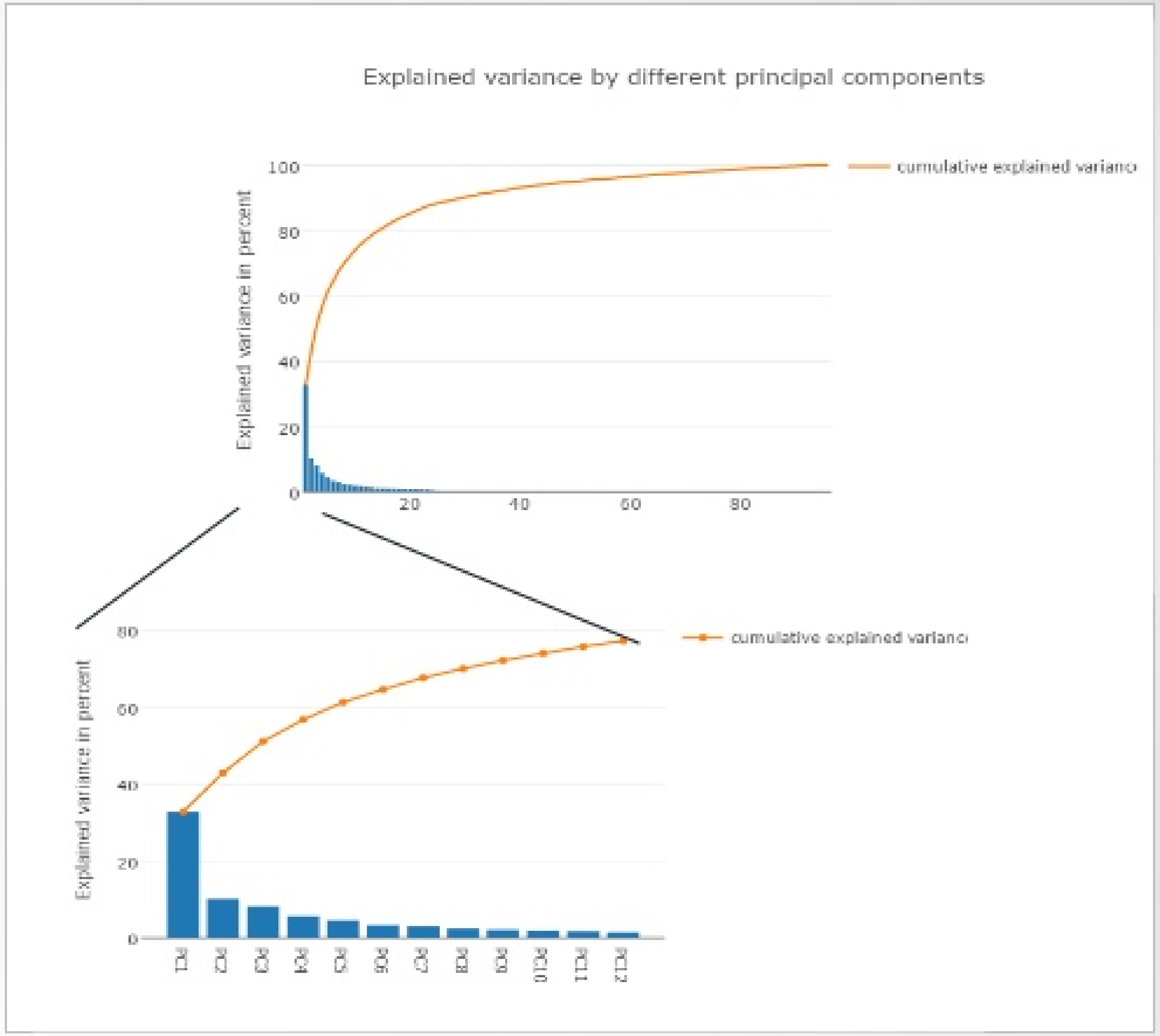
Interpreting PCA as Change of Basis



PCA reference: https://arxiv.org/pdf/1404.1100.pdf

Principal Components & Captured Variance





Warning:

Uncaptured Variance is strictly lost from the predictive model

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Why Reduce Label Dimension?

- The noise reduction and correlations between values captured by reducing to principal components adds more value than variance lost
- Apache Spark ML API doesn't support n-Dimensional regression so k dimensional regression is computationally efficient for k<<n
- Since the 95% of the variance is captured by only the first few principal components there is little to no loss in modelling accuracy (we'll come back to this)
- Independent Component Analysis (ICA) would be even better than PCA because value chained regressors are treated as independent variables. ICA not yet available in Spark ML

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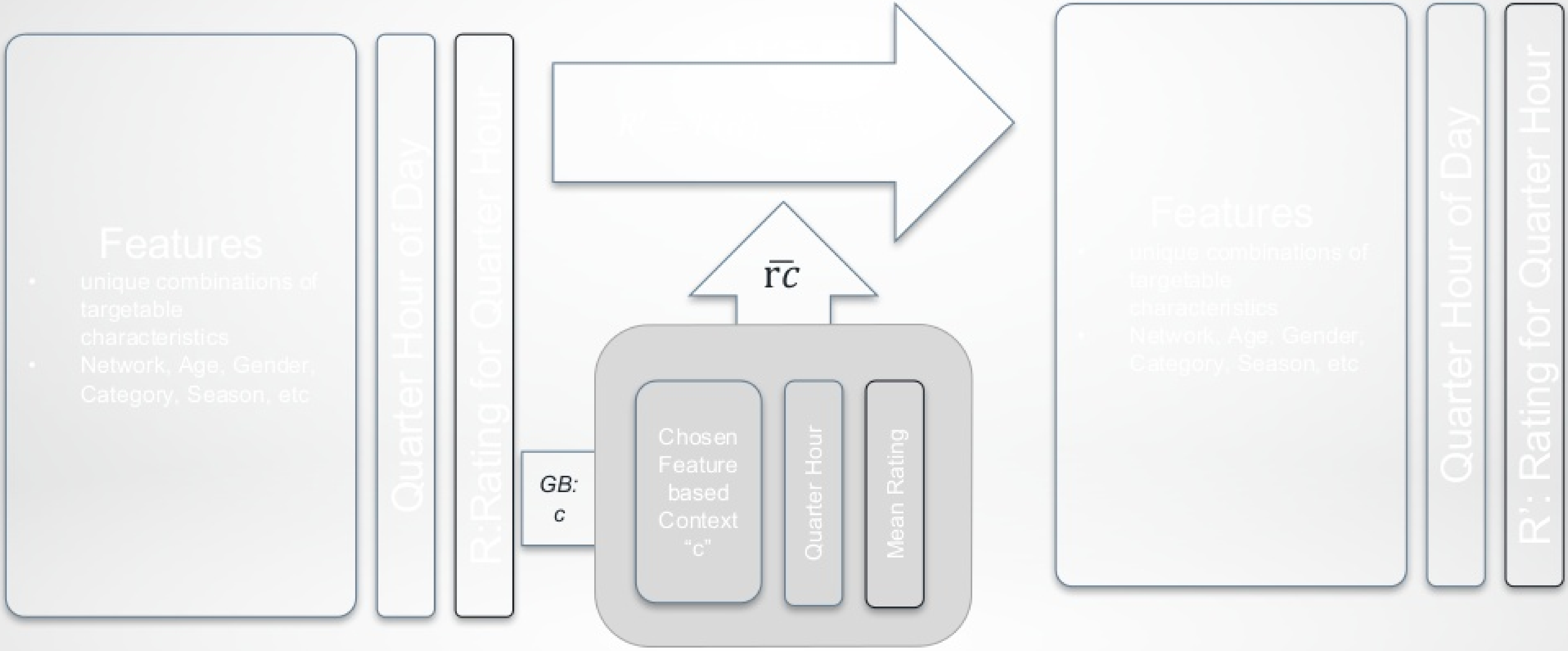
Local Means Coordinate Transform



Store values $c: \overline{\mathrm{r}c}$

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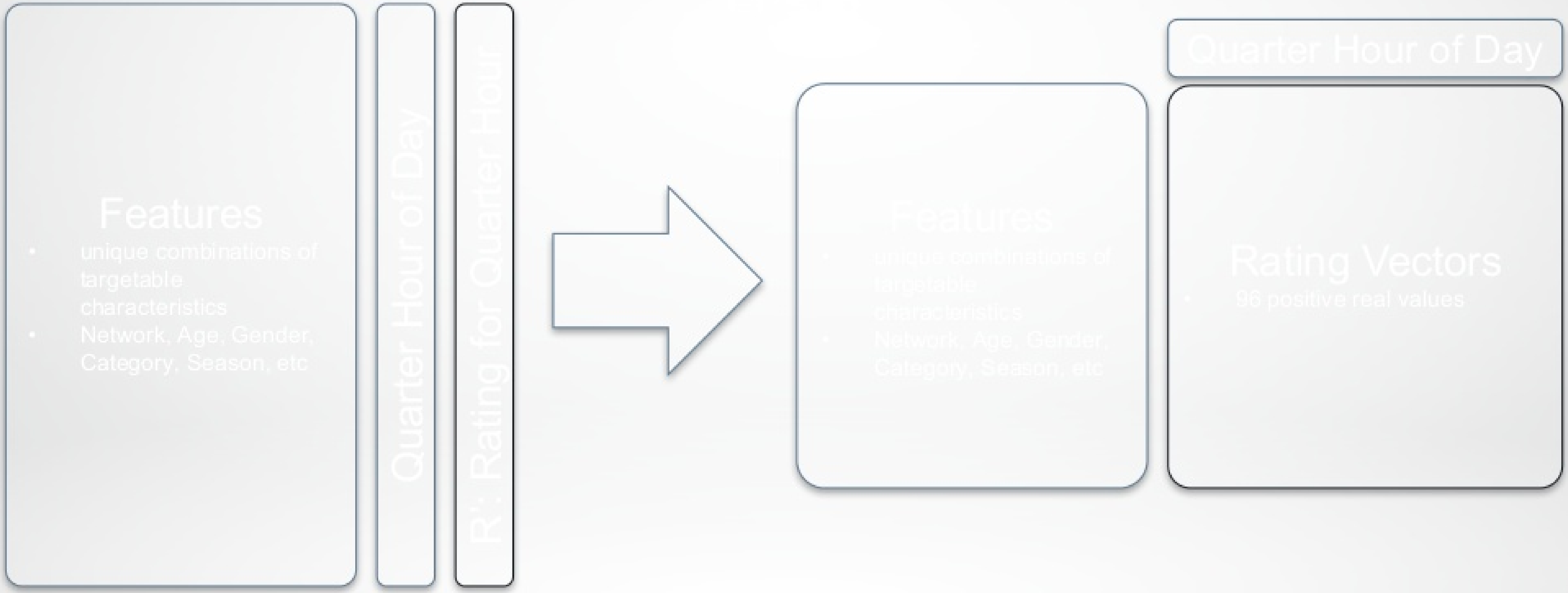
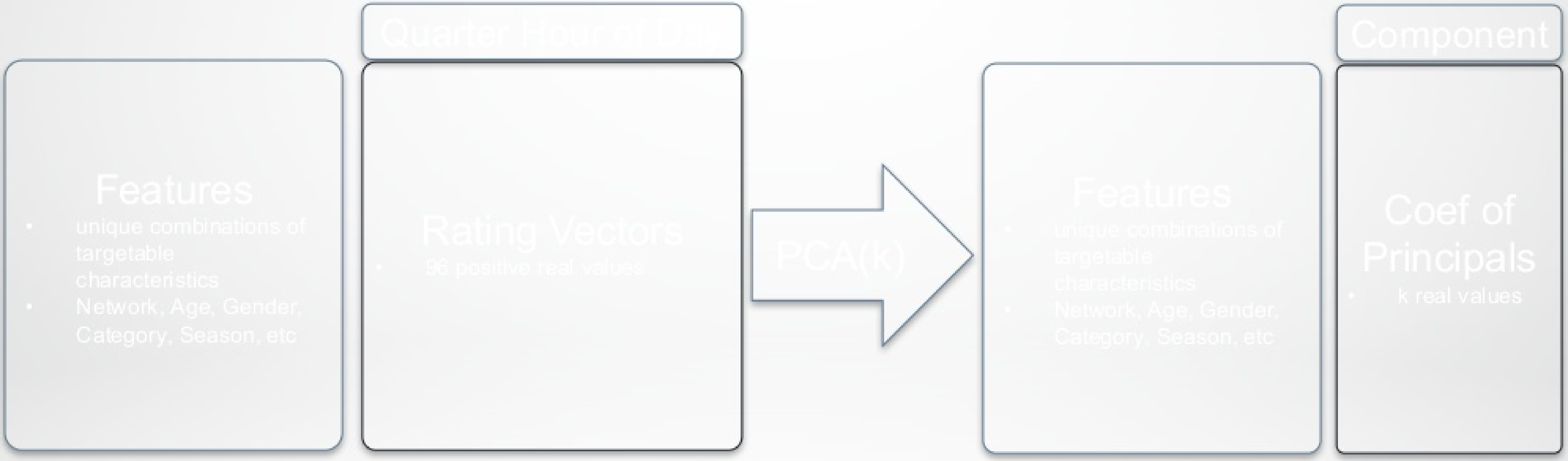
Pivot our Data into to Vectors (day profiles)



Label Dimensionality Reduction



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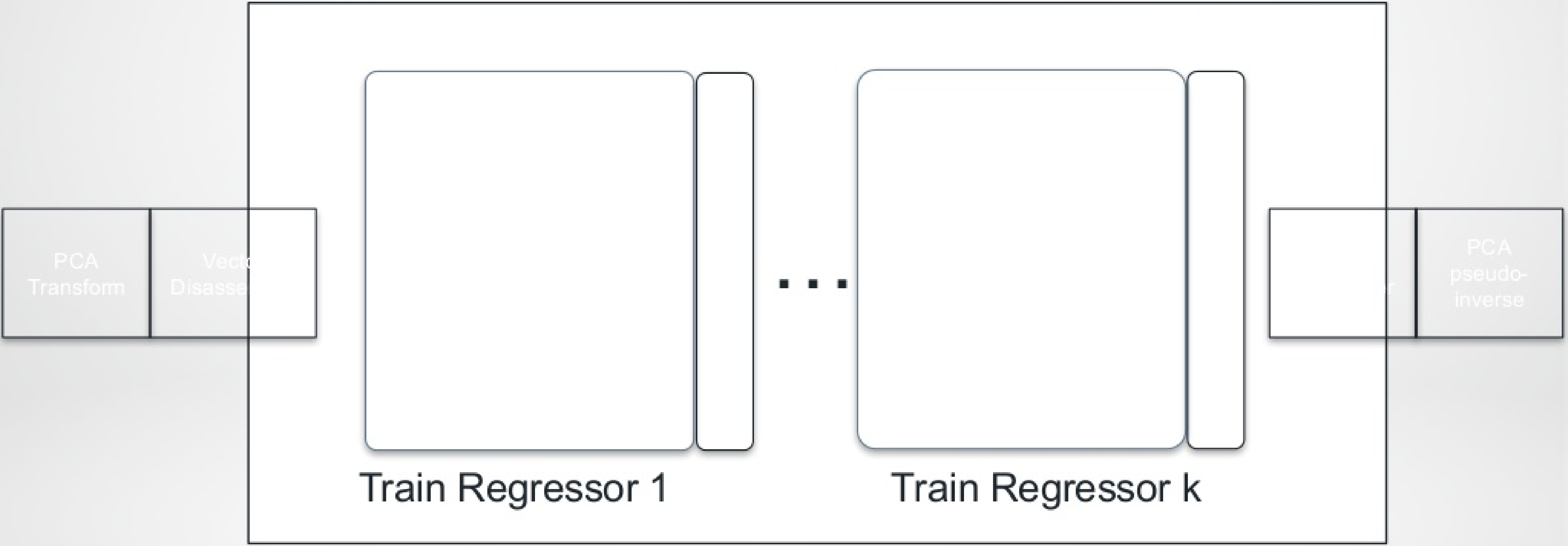
Principal Component Analysis (PCA): to reduce the dimensionality of the problem

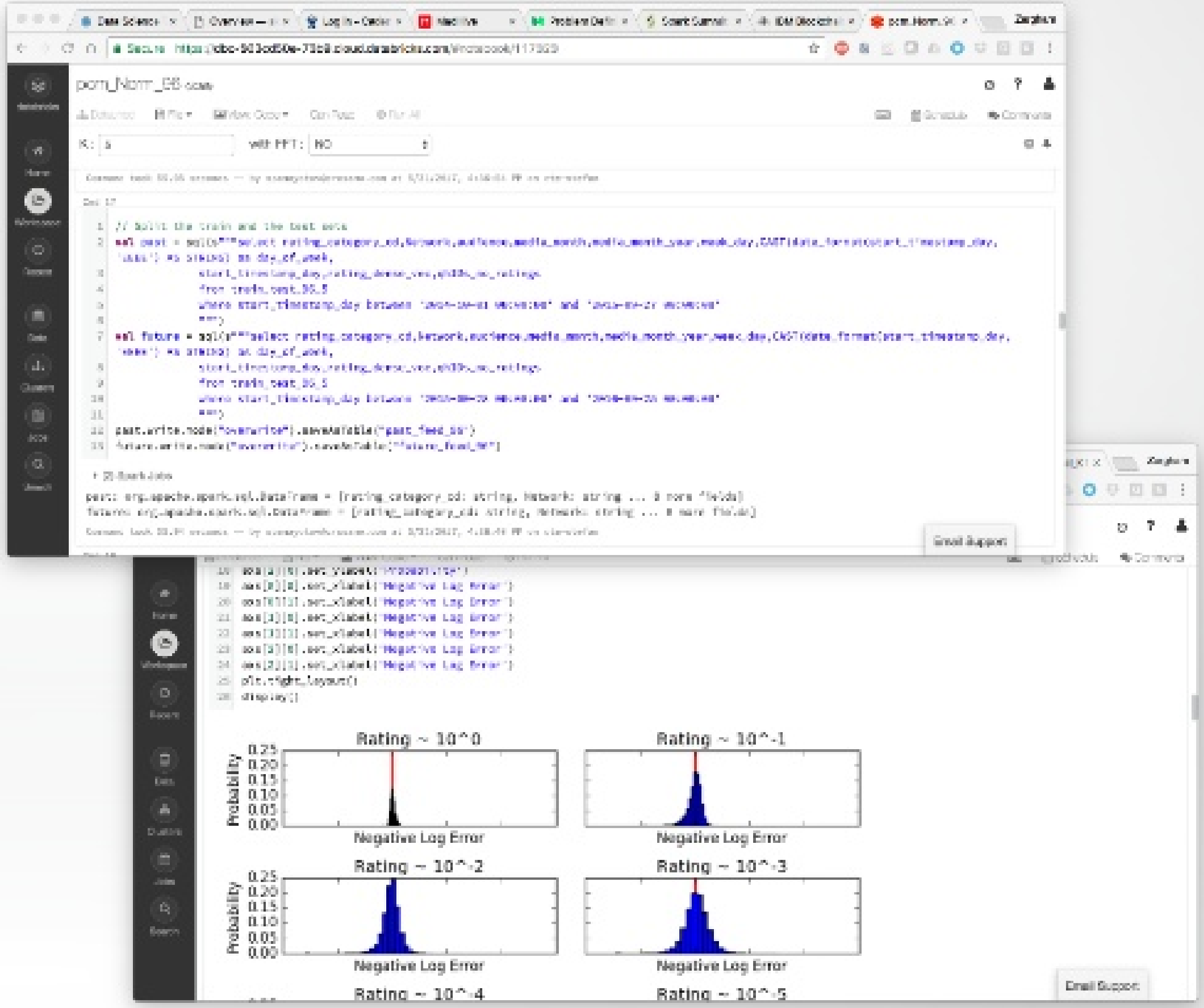


Pipeline of k single label regression models

PRACTICE: Code Demonstration

Technical Breakout to DataBricks Notebook

- Data preparation
  - Ratings Local Coordinate Transformation
  - Vectorization
- ML Pipeline creation and Execution
  - Custom Transformers and Estimators
    - DropColumnsStage
    - PCA2 (show the Scala and pyspark versions)
  - Custom UDFs
    - Used for Vector Disassembler
    - Used for Pseudo-inverse PCA
  - Train & Test
    - Undo custom Coordinate transforms to evaluate
- Results
  - Show Code for Model evaluation
  - Review some Graphical results
- Aside:
  - PySpark Version



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Preliminary Experimental Results

Data= ~6 Million (96 dimensional Vectors) and associated features

Data Size: 6.6 GB

- 20 workers each with 60 GB RAM and 8 cores
- Auto-scaling on

1	Type of model	Output table	Mean Absolute Error	Mean Squared Error	Fit run time	Save results
10	Prime time GBT K=12 net='TOTUS'	sdp_pcm_scatter_totusK12	0.051550236282	0.004443057429	5.84 min	13.59 sec
11	Prime time GBT K=12 norm	sdp_pcm_scatter2_normK12	0.148781770718	0.046845610136	15.66 min	28.36 sec
12	Prime time GBT K=10 norm	sdp_pcm_scatter2_normK10	0.148794481149	0.046891953196	12.95 min	26.36 sec
13	Prime time GBT K=7 norm	sdp_pcm_scatter2_normK7	0.148803329706	0.046886333718	9.47 min	20.08 sec
14	Prime time GBT K=5 norm	sdp_pcm_scatter2_normK5	0.148810023187	0.046904766631	13.88 min	17.24 sec
15	Prime time GBT K=4 norm	sdp_pcm_scatter2_normK4	0.148701796246	0.046768072815	9.02 min	24.31 sec
16	Prime time GBT K=3 norm	sdp_pcm_scatter2_normK3	0.148707072380	0.046826602934	4.73 min	11.05 sec
17	Prime time GBT K=2 norm	sdp_pcm_scatter2_normK2	0.148578846543	0.046695984573	3.80 min	12.09 sec
18	Prime time GBT norm no PCA	sdp_pcm_scatter2_normNoPCA	0.149369025754	0.047247526585	16.36 min	1.06 min
19	All time GBT norm K=12	sdp_pcm_scatter2_normAllK12	0.182586621908	0.071583207654	18.28 min	55.34 sec
20	All time GBT norm K=10	sdp_pcm_scatter2_normAllK10	0.182568372666	0.071576049525	13.52 min	30.75 sec
21	All time GBT norm K=7	sdp_pcm_scatter2_normAllK7	0.182582849778	0.071581692237	9.76 min	25.66 sec
22	All time GBT norm K=5	sdp_pcm_scatter2_normAllK5	0.182533610345	0.071509864673	7.33 min	23.81 sec
23	All time RF norm K=12	sdp_pcm_scatter2_normRFAllK12	0.182181487460	0.070974080041	10.41 min	2.09 min
24	All time RF norm K=10	sdp_pcm_scatter2_normRFAllK10	0.182190370610	0.070988125093	9.59 min	1.76 min
25	All time RF norm K=7	sdp_pcm_scatter2_normRFAllK7	0.182155097088	0.070941472845	5.86 min	45.28 sec
26	All time RF norm K=5	sdp_pcm_scatter2_normRFAllK5	0.182228954649	0.070978910337	3.87 min	1.17 min

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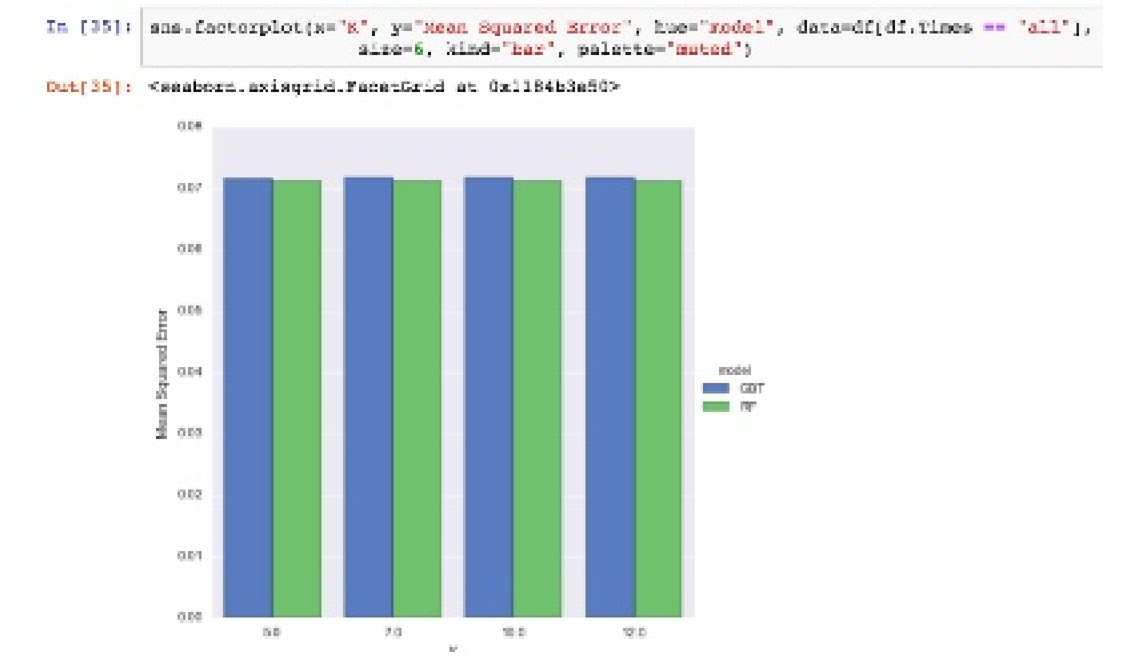
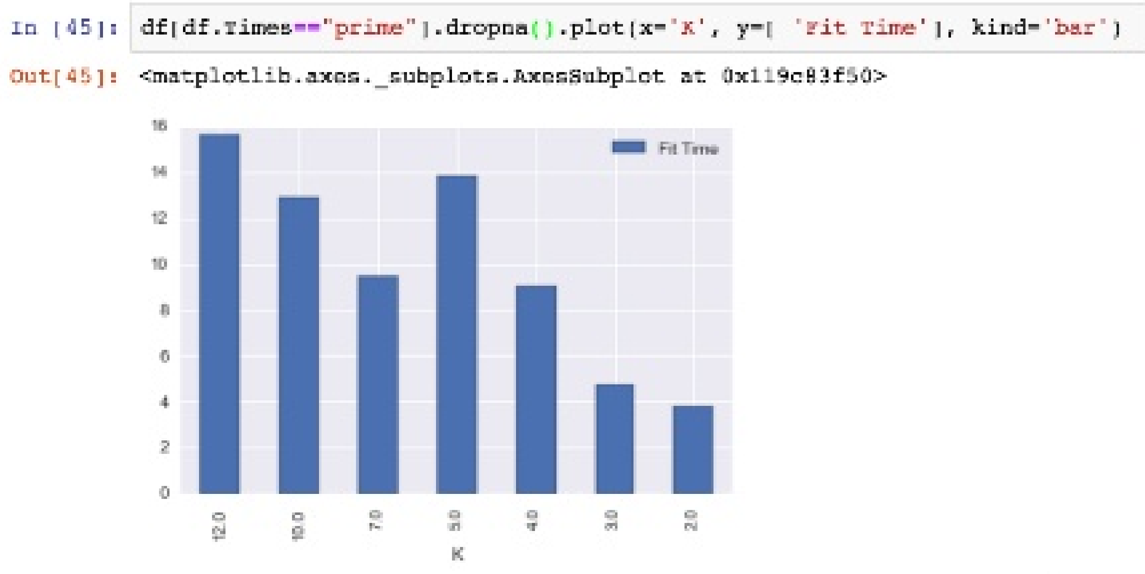
Insights from Initial Results

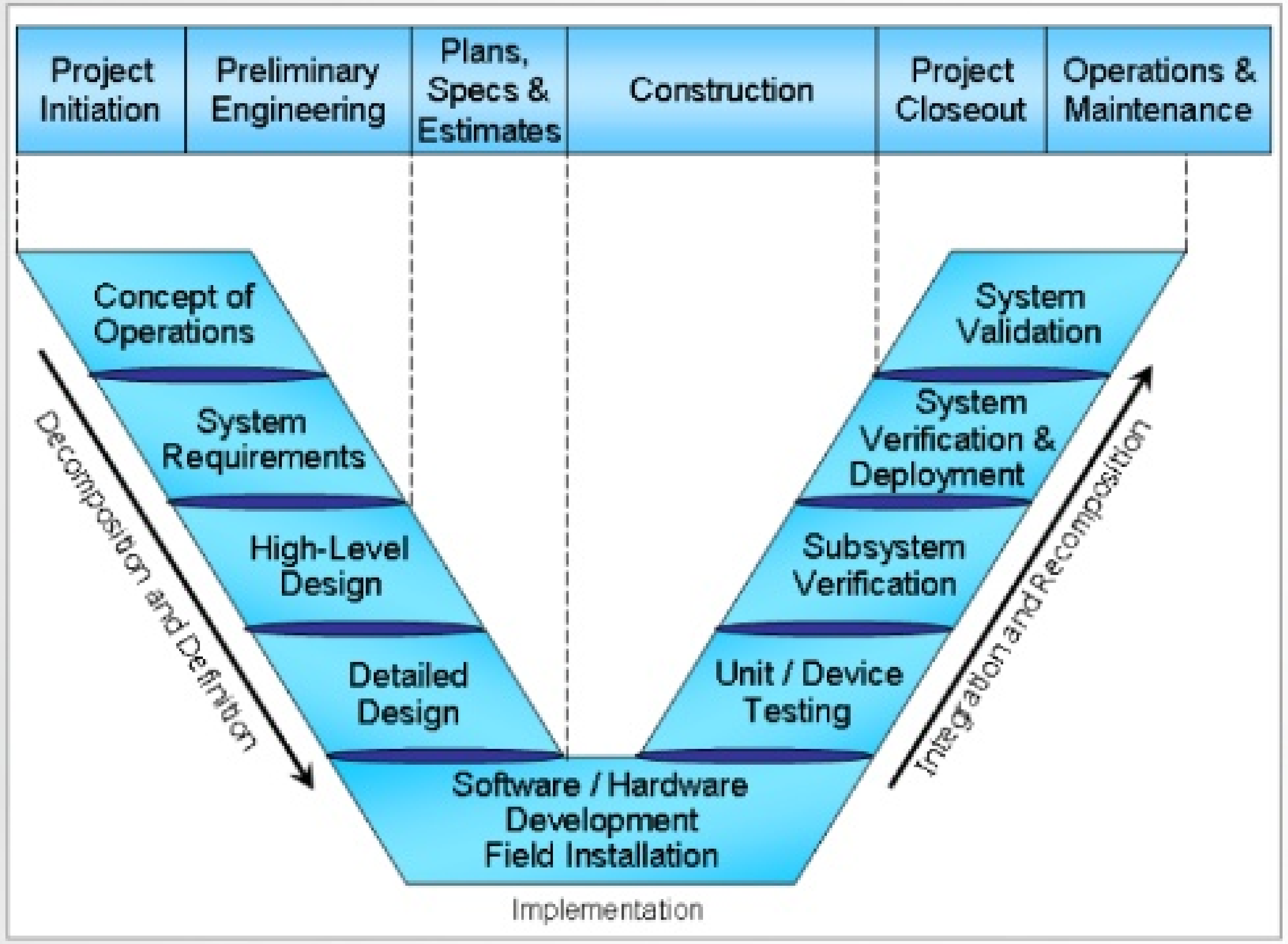
- Support for arbitrary Regression model class
  - Comparable results with Gradient Boosted Trees and Random Forests
- Daily Ratings Phenomenon is actually low Rank
  - No Measureable loss in accuracy as we reduce from K=12 to K=5 for the n=96 dimensional version
  - No Measureable loss in accuracy as we reduce from K=12 to K=2 for the n=12 dimensional version
- Reducing the number of dimensions saves runtime
  - More experiments are needed but preliminary results are still significant
- Inclusion of PCA when K=n provides no measureable improvement
  - Tested with K=n=12
  - Would like to test with ICA instead of PCA
- Next Steps:
  - More exhaustive repeated trials for run times
  - Further reduce K until we start to see performance degrade





Monitoring & Maintaining Machine Learning Models

Validation and Verification



IEEE 1012-2012 standard definition of Validation and Verification

Validation: The assurance that a product, service, or system meets the needs of the customer and other identified stakeholders. It often involves acceptance and suitability with external customers.

What did it do?

Verification: The evaluation of whether or not a product, service, or system complies with a regulation, requirement, specification, or imposed condition.
It is often an internal process.

How well did it do it?

System design, implementation and test (QA) are only part of the system acquisition process

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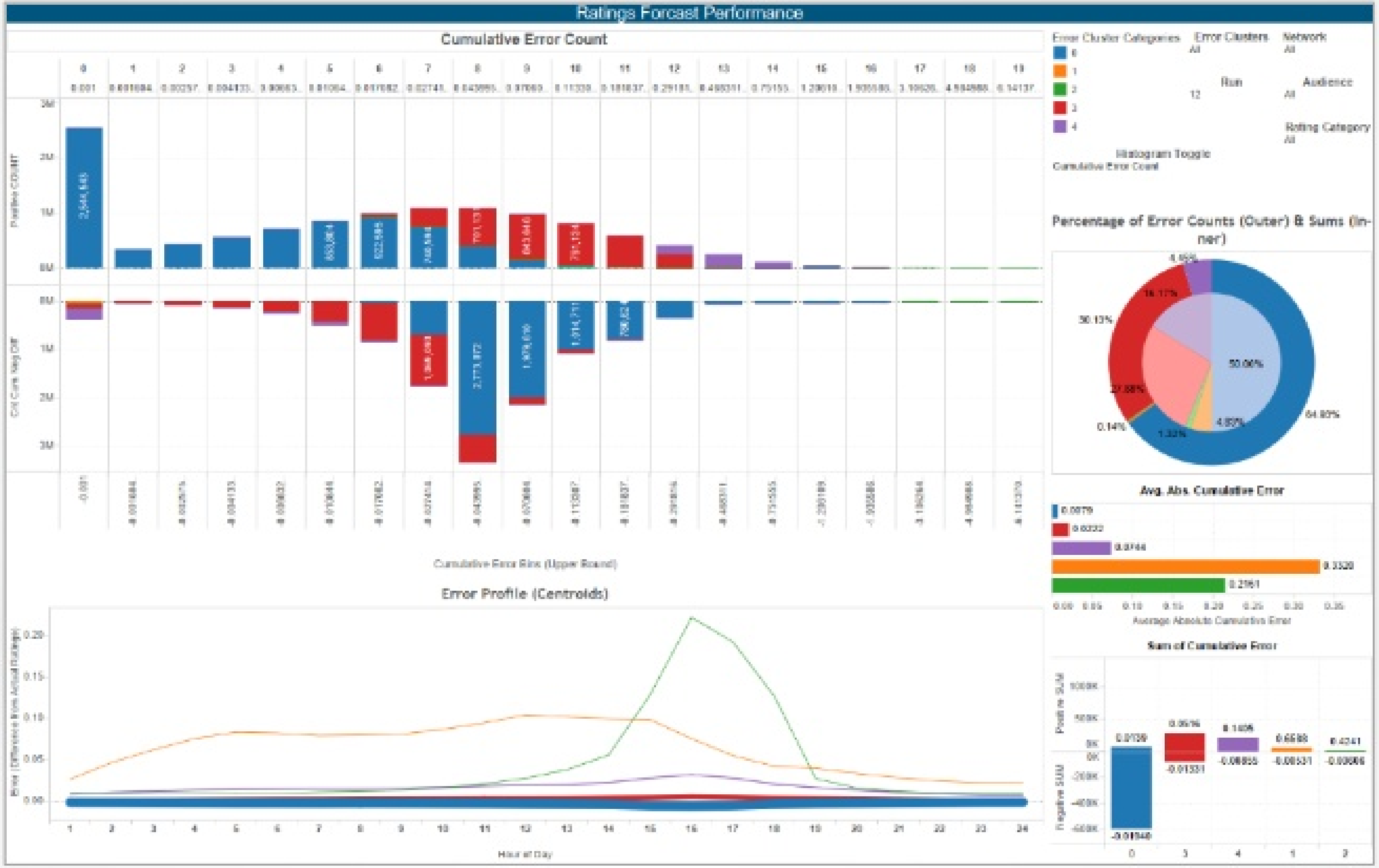
Validation of Ratings via Performance Dashboard



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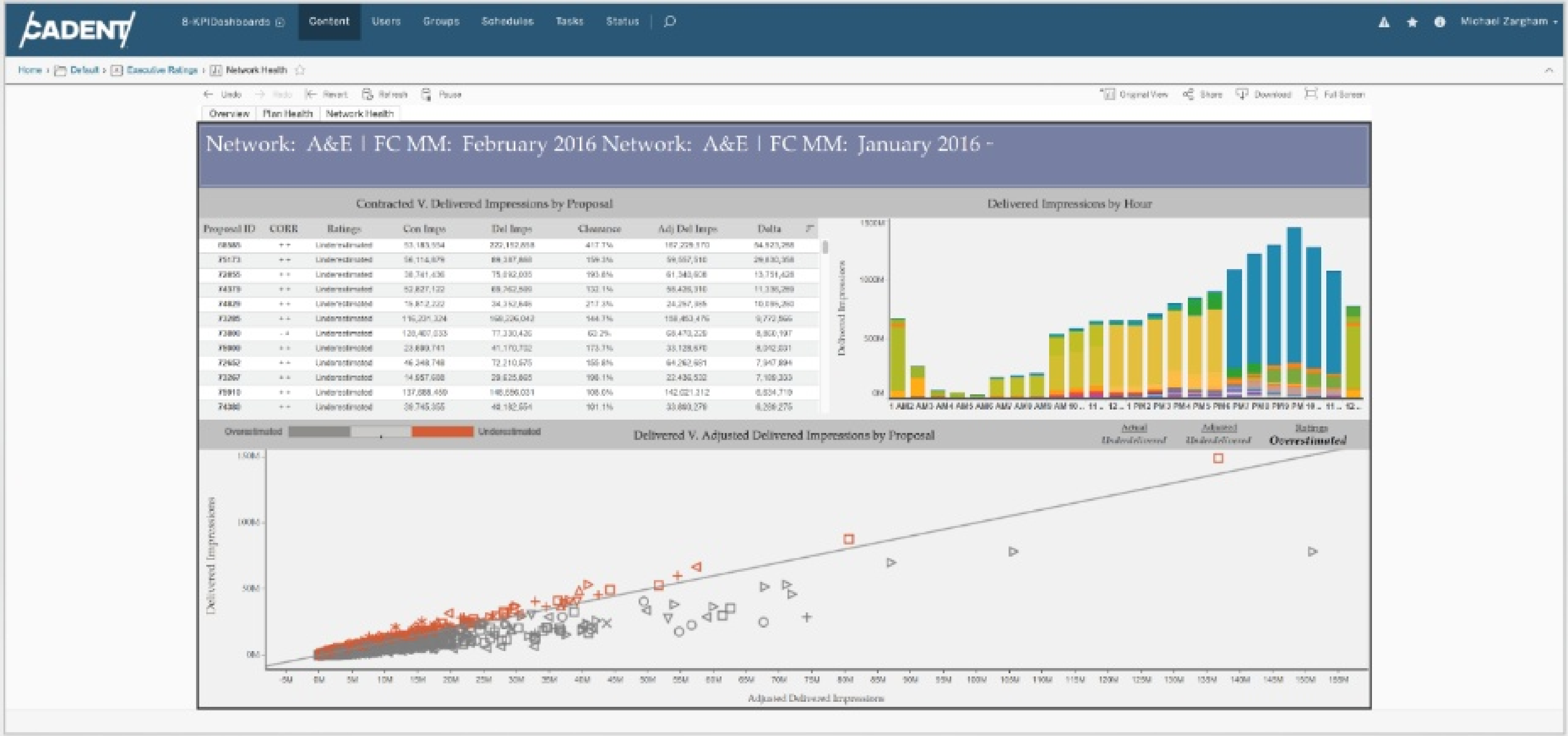
Verification of Ratings via Delivery KPI Dashboard



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WRAP UP

Other Projects

- Video on Demand Campaign Management
  - Forecasting Supply, Demand and Competition
  - Yield Management: Dynamic Inflight Optimization (feedback controller)
  - Pricing and Packaging of Inventory
- Extending Linear Advertising
  - Targeted Advertising Insertions in Linear Cable
  - Addressable Backfill for Linear Cable
  - Multicast Advertising on Broadcast Stations
- Unified Unicast/Multicast Advertising
  - Cross Platform Audience Based Planning
  - Flexible Hybrid-cloud Data Platform

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Thank You.

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