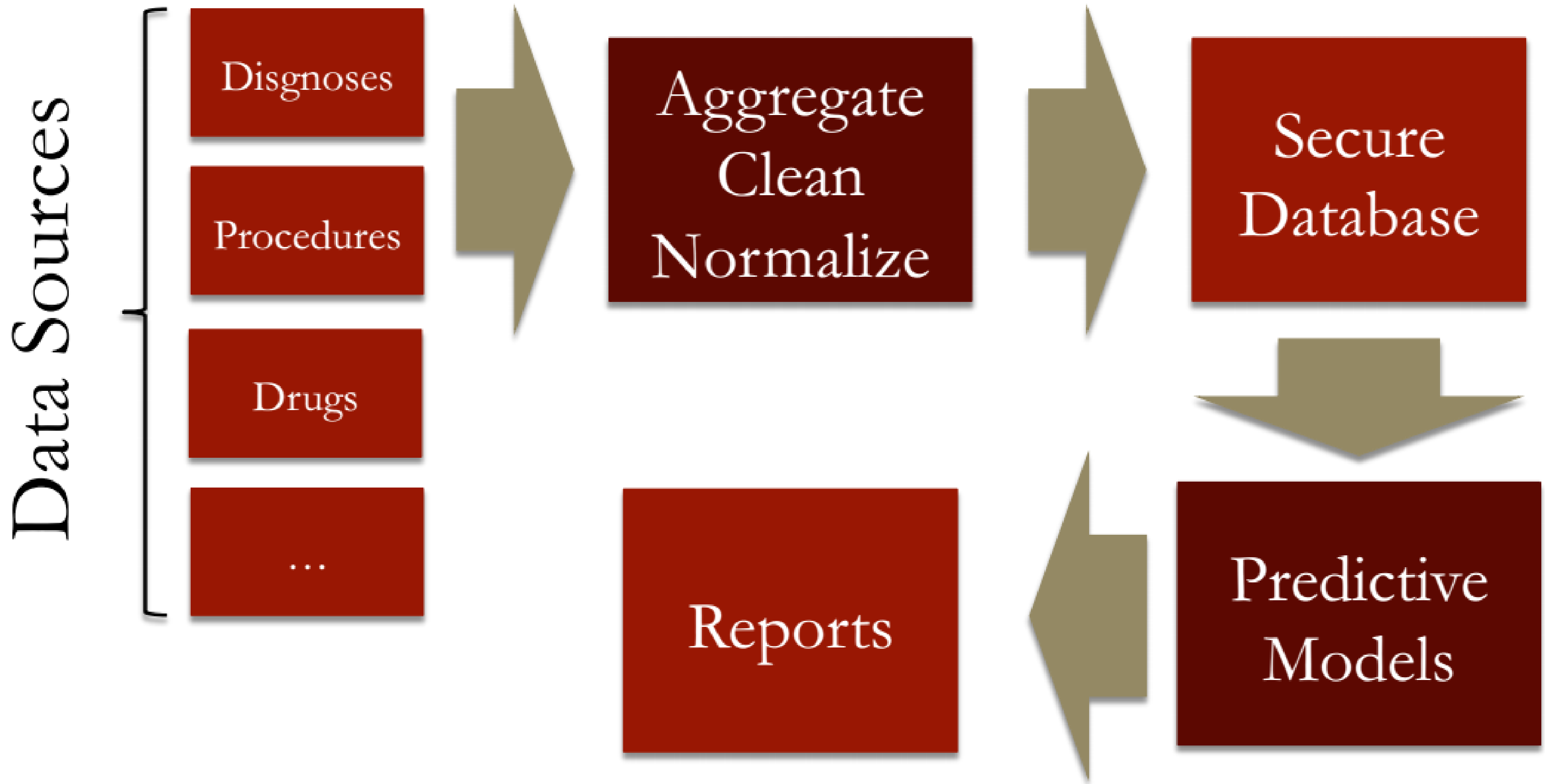
KEEPING AN EYE ON HEALTHCARE COSTS

The D2Hawkeye Story

D2Hawkeye

- Founded by Chris Kryder, MD, MBA in 2001
- Combine expert knowledge and databases with analytics to improve quality and cost management in healthcare
- Located in Massachusetts USA, grew very fast and was sold to Verisk Analytics in 2009

D2Hawkeye


Data Sources
Disgnoses
Procedures
Drugs
...
Aggregate
Clean
Normalize
Secure
Database
Predictive
Models
Reports

Healthcare Case Management

- D2Hawkeye tries to improve healthcare case management
  - Identify high-risk patients
  - Work with patients to manage treatment and associated cost
  - Arrange specialist care
- Medical costs often relate to severity of health problems, and are an issue for both patient and provider
- Goal: improve the quality of cost predictions

Impact

- Many different types of clients
  - Third party administrators of medical claims
  - Case management companies
  - Benefit consultants
  - Health plans

- **Millions of people** analyzed monthly through analytic platform in 2009
- **Thousands of employers** processed monthly

Pre-Analytics Approach

- Human judgment - MDs manually analyzed patient histories and developed
- Limited data sets
- Costly and inefficient
- Can we use analytics instead?

Quick Question

- In what ways do you think an analytics approach to predicting healthcare cost will improve upon the previous approach of human judgment? Select all that apply.

- [ ] It will allow D2Hawkeye to analyze millions of patients.
- [ ] It will allow D2Hawkeye to make predictions faster than doctors can.
- [ ] It will allow D2Hawkeye use all available data (millions of cases) to make decisions.

Claims Data

Data Sources

- Healthcare industry is data-rich, but data may be hard to access
  - Unstructured - doctor's notes
  - Unavailable - hard to get due to differences in technology
  - Inaccessible - strong privacy laws around healthcare data sharing
- What is available?

Data Sources

- Claims data
  - Requests for reimbursement submitted to insurance companies or state-provided insurance from doctors, hospitals and pharmacies.
- Eligibility information
- Demographic information

Claims Data

ClaimType	ProviderName	DiagCode	DiagDesc	Source DiagCode	SourceDiagDesc	ProcNDC Code	ProcNDCDesc	ServiceDate	PaidAmount
DEN	SOUTHEASTERN MINNESOTA ORAL & MAX	DD0238	Dental Diseases	5206	Unspecified Anomaly of Tooth Position	DD007	Anesthesia - General	4/22/2005	$ -
DEN	ASSOCIATED ORAL & MAXILLOFACIAL SURGEONS PA	DD0238	Dental Diseases	5206	Disturbances in ToOther Eruption	DD025	Dental	7/8/2005	$ 272.68
DEN	CENTRAL FLORIDA ORAL SURGERY	DD0238	Dental Diseases	5206	Disturbances in ToOther Eruption	DD025	Dental	11/11/2005	$ 568.13
Med	ALPHARETTA INTERNA	DD0004	ENT and Upper Resp Disorders	4610	Acute Maxillary Sinusitis	DD147	Office Visit - Established Patient	5/26/2005	$ 125.85
Med	CUMMING FAMILY MEDICINE	DD0170	Neurotic and Personality Disorders	30000	Neurotic Disorders-30000	DD149	Office Visit - New Patient	6/20/2005	$ -
Med	ATLANTA WOMENS HEALTH GROUP-582483738.20	DD0102	Screening	V776	Special Screening for Cystic Fibrosis	DD077	Lab - Blood Tests	7/29/2005	$ 1.52

Claims Data

- Rich, structured data source
- Very high dimension
- Doesn't capture all aspects of a persons treatment or health - many things must be inferred
- Unlike electronic medical records, we do not know the results of a test, only that a test was administered

D2Hawkeye's Claims Data

- Available: claims data for **2.4 million people** over a span of **3 years**

"Observation" Period 2001-2003	"Results" Period 2003-2004

- Include only people with data for at least 10 months in both periods - **400,000 people**

Quick Question

- A common problem in analytics is that you have some data available, but it's not the ideal dataset. This is the case for this problem, where we only have claims data. Which of the following pieces of information would we ideally *like to have* in our dataset, but are *not included* in claims data? (Select all that apply.)

- [ ] Blood test results
- [ ] Drugs prescribed to the patient
- [ ] Physical exam results (weight, height, blood pressure, etc.)

Variables

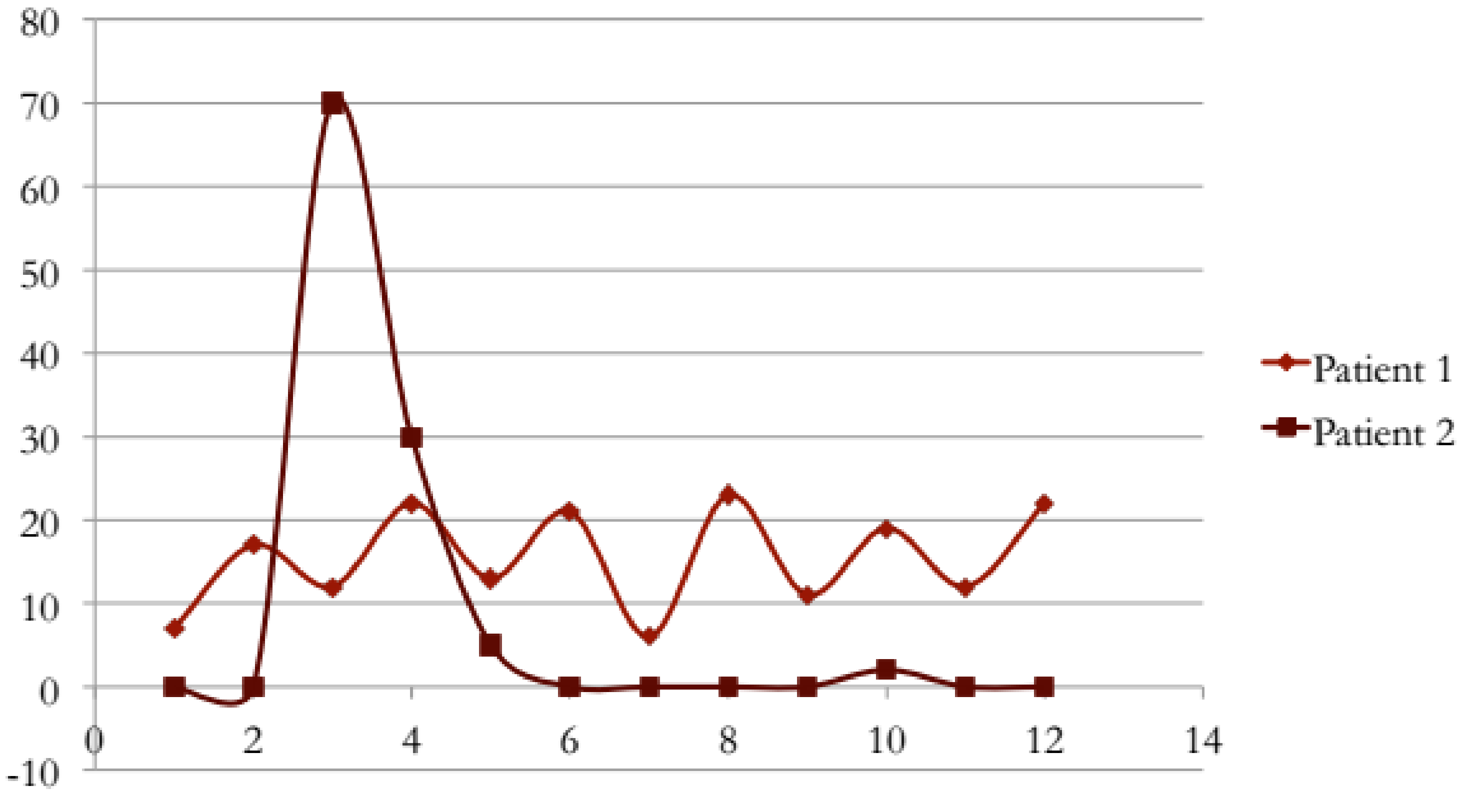
Variables

13,000 diagnoses → 217 diagnosis groups

22,000 procedures → 213 procedure groups

45,000 prescription drugs → 189 therapeutic groups

Variables - Cost Profiles

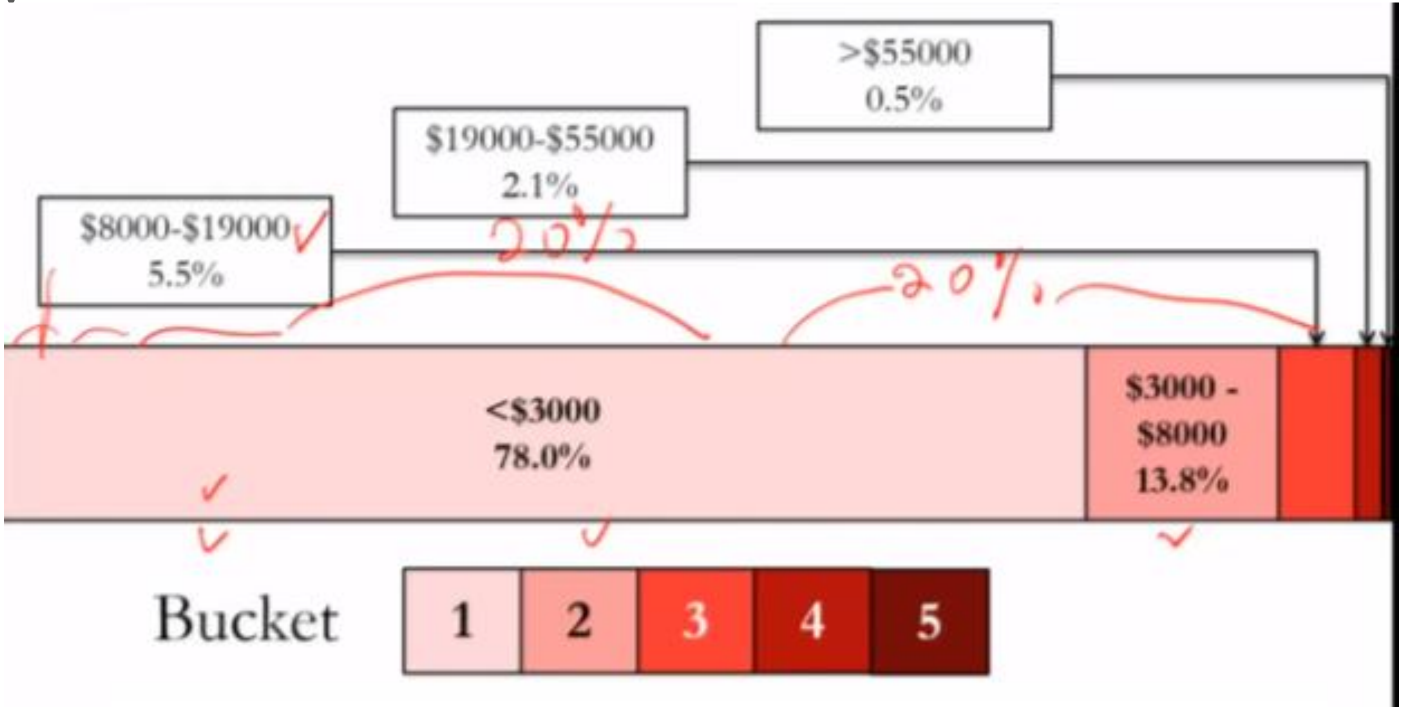


Additional Variables

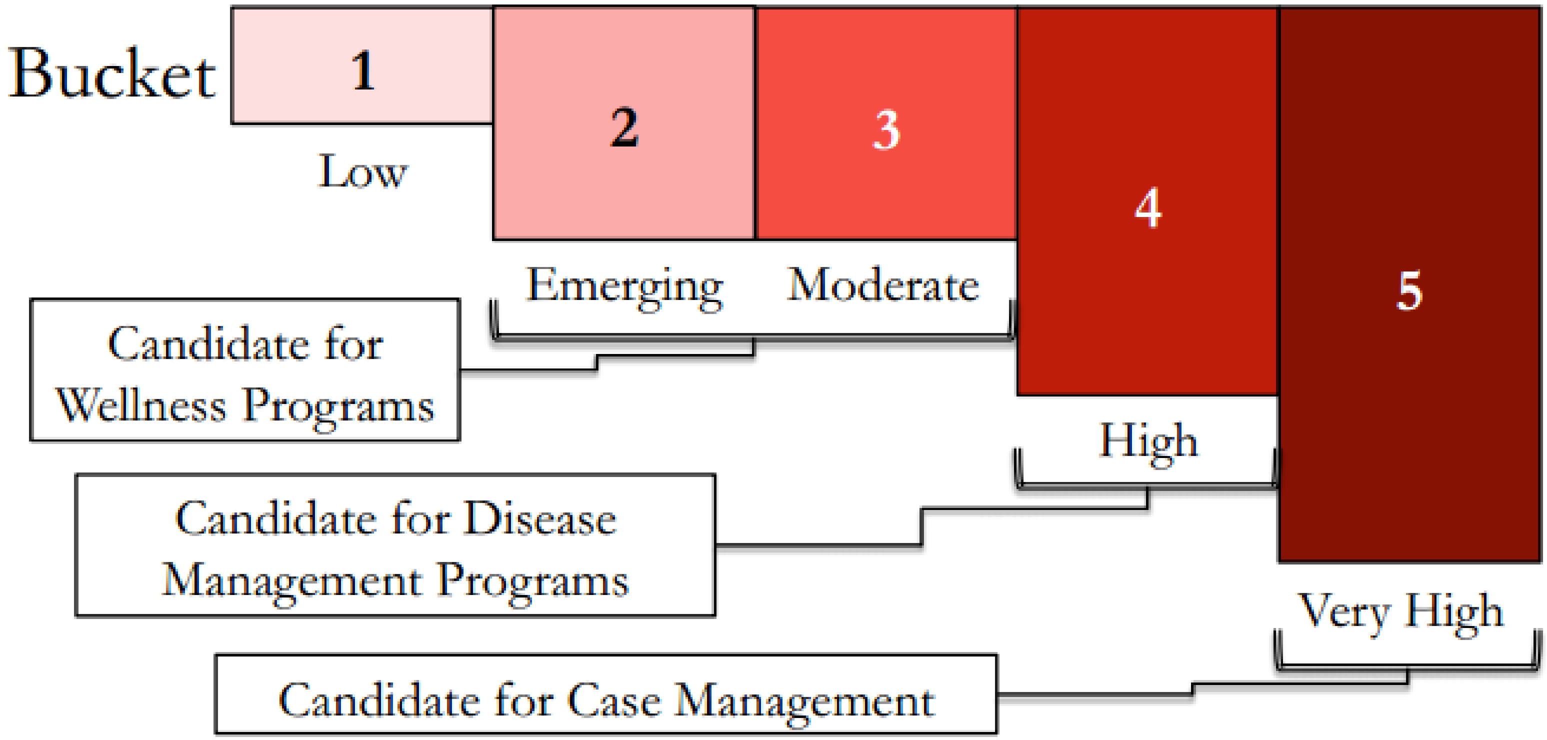
- Chronic condition cost indicators
- 269 medically defined risk rules
  - Interactions between illnesses
  - Interactions between diagnosis and age
  - Noncompliance to treatment
  - Illness severity
- Gender and age

Cost Variables

- Rather than using cost directly, we bucket costs and consider everyone in the group equal.



Medical Interpretation of Buckets



Quick Question

- While we don't have all of the data we would ideally like to have in this problem (like test results), we can define new variables using the data we do have. Which of the following were new variables defined to help predict

- [ ] Variables to capture chronic conditions
- [ ] Noncompliance to treatment
- [ ] Illness severity
- [ ] Interactions between illnesses

Error Measures

Error Measures

- Typically we use R2 or accuracy, but others can be used
- In case of D2Hawkeye, failing to classify a **high-cost patient** correctly is **worse** than failing to classify a **low-cost patient** correctly
- Use a “penalty error” to capture this asymmetry

Penalty Error

- Key idea: use asymmetric penalties
- Define a "penalty matrix" as the cost of being wrong

		Outcome				
		1	2	3	4	5
Forecast	1	0	2	4	6	8
	2	1	0	2	4	6
	3	2	1	0	2	4
	4	3	2	1	0	2
	5	4	3	2	1	0

Baseline

- Baseline is to simply predict that the cost in the next "period" will be same as the cost in the current period
- Accuracy of 75%
- Penalty Error of 0.56

Quick Question

- The image below shows the penalty error matrix that we discussed before

		Outcome				
		1	2	3	4	5
Forecast	1	0	2	4	6	8
	2	1	0	2	4	6
	3	2	1	0	2	4
	4	3	2	1	0	2
	5	4	3	2	1	0

- We can interpret this matrix as follows. Suppose the actual outcome for an observation is 3, and we predict 2. We find 3 on the top of the matrix, and go down to the second row (since we forecasted 2). The penalty error for this mistake is 2. If for another observation we predict (forecast) 4, but the actual outcome is 1, that is a penalty error of 3.

Quick Question

- What is the worst mistake we can make, according to the penalty error matrix?

  - ○ We predict 5 (very high cost), but the actual outcome is 1 (very low cost).
  - ○ We predict 1 (very low cost), but the actual outcome is 5 (very high cost).

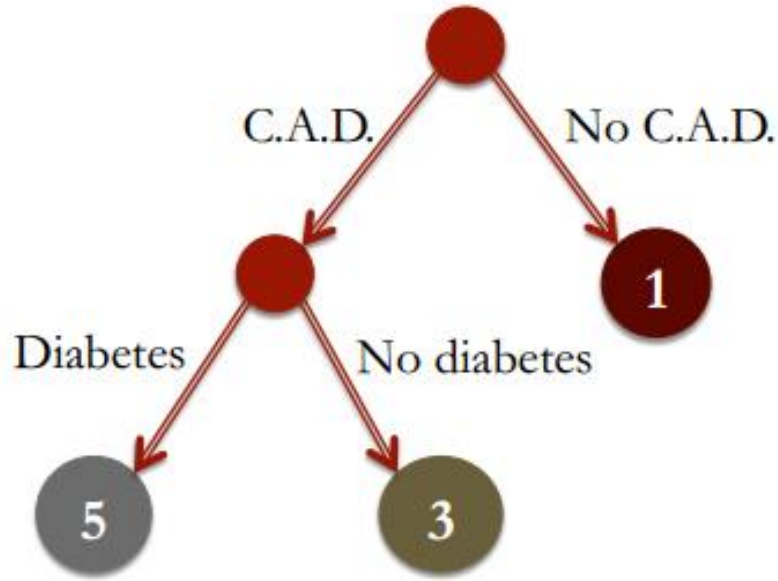
- What are the "best" types of mistakes we can make, according to the penalty error matrix?

  - ○ Mistakes where we predict one cost bucket HIGHER than the actual outcome.
  - ○ Mistakes where we predict one cost bucket LOWER than the actual outcome.

CART to Predict Cost

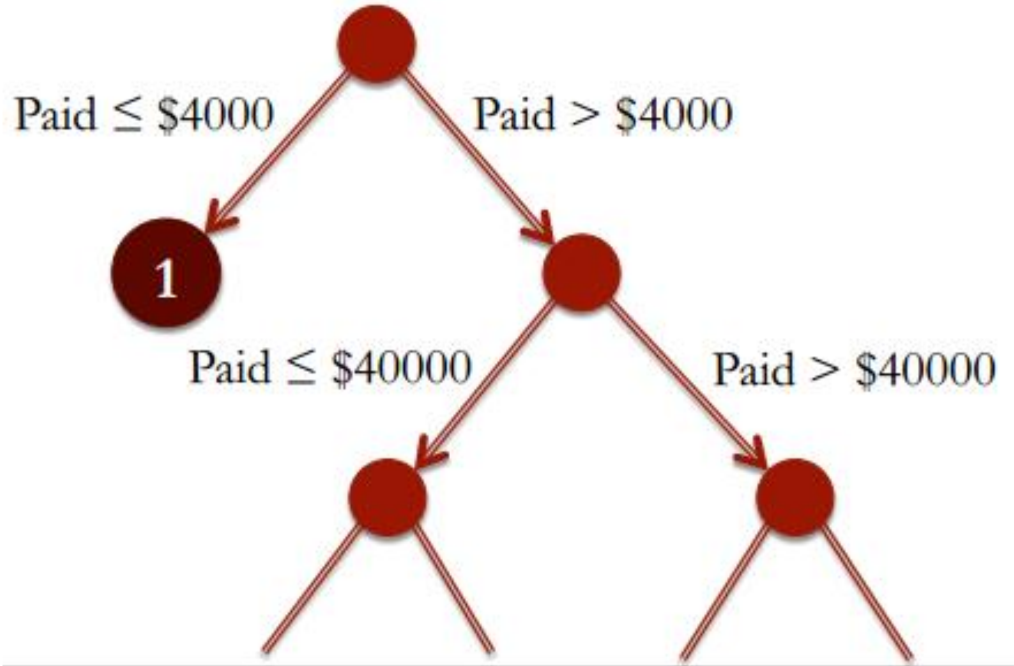
Multi-class Classification

- We are predicting a bucket number
- Example



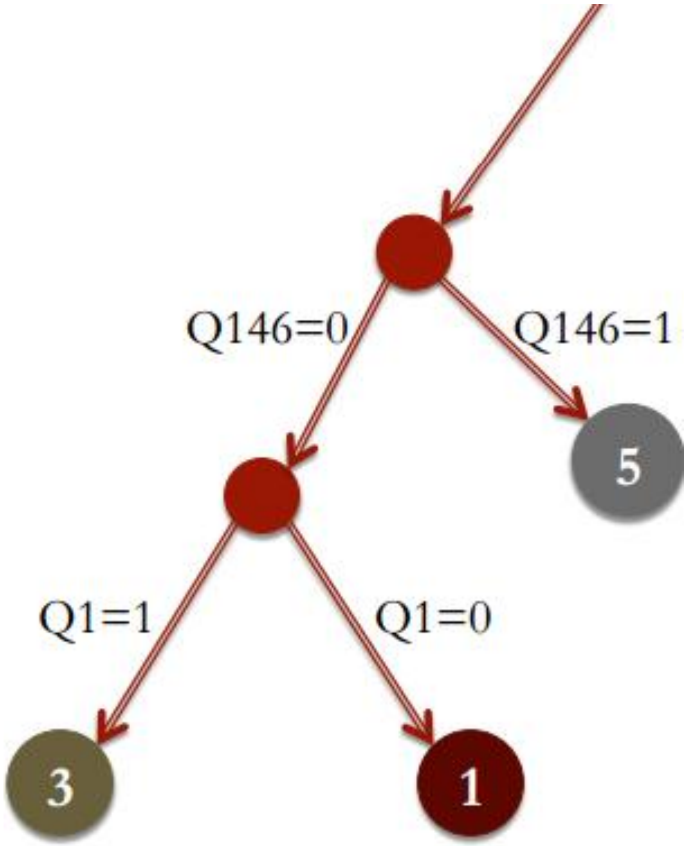
Most Important Factors

- First splits are related to cost



Secondary Factors

- Risk factors
- Chronic Illness
- **“Q146”**
  - Asthma + depression
- **“Q1”**
  - Risk factor indicating hylan injection
  - Possible knee replacement or arthroscopy



Example Groups for Bucket 5

- Under 35 years old, between $3300 and $3900 in claims, C.A.D., but no office visits in last year
- Claims between $3900 and $43000 with at least $8000 paid in last 12 months, $4300 in pharmacy claims, acute cost profile and cancer diagnosis
- More than $58000 in claims, at least $55000 paid in last 12 months, and not an acute profile

Quick Question

- What were the most important factors in the CART trees to predict cost?

- ○ Cost ranges from the previous year
- ○ Risk factors
- ○ Chronic conditions
- ○ Number of office visits last year

Claims Data in R

RMD

- Refer to Rmarkdown file for the code.

Quick Question

- What is the average age of patients in the training set, ClaimsTrain?
- What proportion of people in the training set (ClaimsTrain) had at least one diagnosis code for diabetes?

Baseline Method and Penalty Matrix

RMD file

- Refer to the RMD file for details.

Quick Question

Suppose that instead of the baseline method discussed, we used the baseline method of predicting the most frequent outcome for all observations. This new baseline method would predict cost bucket 1 for everyone.

- What would the accuracy of this baseline method be on the test set?
- What would the penalty error of this baseline method be on the test set?

Predicting Healthcare Costs in R

Results

	Accuracy		Penalty Error	
Bucket	Trees	Baseline	Trees	Baseline
All	80%	75%	0.52	0.56
1	85%	85%	0.42	0.44
2	60%	31%	0.89	0.96
3	53%	21%	1.01	1.37
4	39%	19%	1.01	1.72
5	30%	23%	1.01	1.88

Insights

- **Substantial improvement** over the baseline
- **Doubled accuracy** over baseline in some cases
- Smaller accuracy improvement on **bucket 5**, but **much lower penalty**

Analytics Provide an Edge

- Substantial improvement in D2Hawkeye's ability to identify patients who need more attention
- Because the model was interpretable, physicians were able to improve the model by identifying new variables and refining existing variables
- Analytics gave D2Hawkeye an edge over competition using "last-century" methods