

# Adding Optimization to Your Analytics Toolbox

Dr. Gwyneth Butera and Dr. Russell Halper



**GUROBI**  
OPTIMIZATION

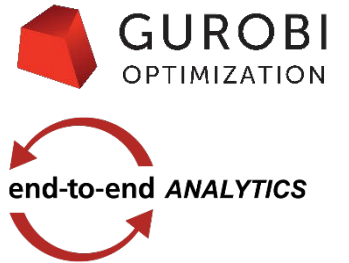
The World's Fastest Solver



end-to-end *ANALYTICS*

# Agenda

- Basics of Optimization and MIP (Mixed Integer Programming)
- Identifying Optimization Problems Within Your Organization
- How MIP Complements Machine Learning



# Basics of Optimization and MIP (Mixed Integer Programming)

Dr. Gwyneth Butera

# Mathematical Optimization Primer



- What do we mean by mathematical optimization?
- What does “optimal” mean?
- Basic form of a mathematical programming problem (MP)

Objective:                    minimize  $c^T x$

Constraints:                 $Ax = b$  (linear constraints)

$l \leq x \leq u$  (bound constraints)

some or all  $x_j$  must take integer values (integrality constraints)

- Many types of MP problems including LP, MIP, QP
- Typical modeling applications

# Basic Mixed-Integer Programming Example

## “Modular” furniture manufacturing

- $b$  – number of bar stools,
- $c$  – number of chairs.

$$\max_{b,c} (10b + 11c)$$

subject to

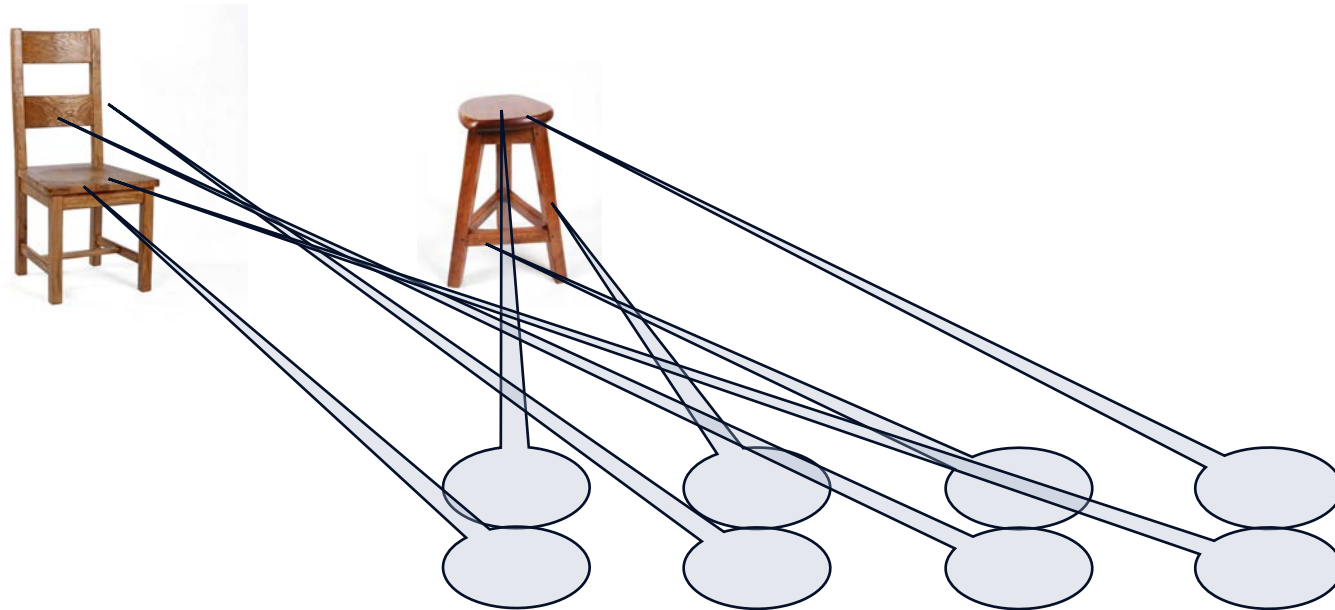
$$b + c \leq 10,$$

$$3b + 4c \leq 36,$$

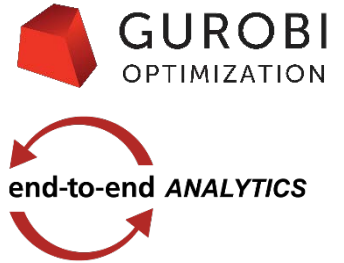
$$3b + 5c \leq 41,$$

$$4b + 2c \leq 35,$$

$$\text{integer } b, c \geq 0$$

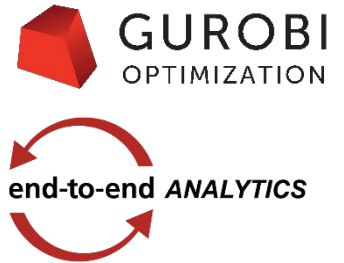


# Sample Formulation: Sports Scheduling Modeling



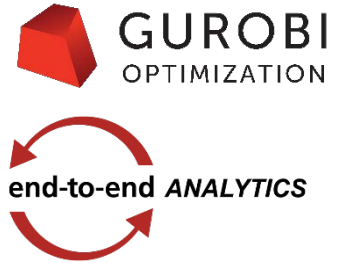
- Given a set of teams and time slots
- Produce a schedule for the matches between teams
- **Goals**
  - Fair and exciting schedule
- **Constraints**
  - Must obey league rules (e.g. number of home/away games)
  - No schedule conflicts (e.g. venue restrictions)
  - Potentially lots of others

# Sports Scheduling: Basic Model



- **Define a set of binary variables  $X$** 
  - $X(i, j, k) = 1$  if team  $i$  plays team  $j$  in week  $k$
  - $X(i, j, k) = 0$  otherwise
- **Translate scheduling rules into linear constraints**
  - Each team plays a game each week
    - $X(i, j_1, 1) + X(i, j_2, 1) + X(i, j_3, 1) + \dots = 1$
  - Each team must eventually play every other team (in league, in division, ...)
    - $X(i, j, 1) + X(i, j, 2) + X(i, j, 3) + \dots = 1$

# Sports Scheduling: Basic Model



**Prohibited games (teams 1 and 4 can't play in week 3)**

- $X(1,4,3) = 0$

**Required games (teams 3 and 5 must play in week 7)**

- $X(3,5,7) = 1$

**No back-to-back division series (1 and 2 can't play week 3 and week 4)**

- $X(1, 2, 3) + X(1, 2, 4) \leq 1$

## Objective

- Given projected TV audience for each game and each week, maximize the total audience



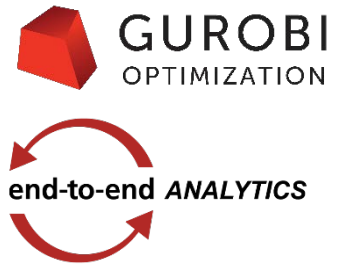
# 2013 NFL Schedule



| DAL | NYG | PHL | WAS | CHI | DET | GB  | MIN | ATL | CAR | NO  | TB  | ARZ | STL | SF  | SEA |    | BUF | MIA | NE  | NYJ | BAL | CIN | CLE | PIT | HOU | IND | JAX | TEN | DEN | KC  | OAK | SD  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| NYG | DAL | WAS | PHI | CIN | MIN | SF  | DET | NO  | SEA | ATL | NYJ | STL | ARZ | GB  | CAR | 1  | NE  | CLE | BUF | TB  | DEN | CHI | MIA | TEN | SD  | OAK | KC  | PIT | BAL | JAC | IND | HOU |
| KC  | DEN | SD  | GB  | MIN | ARZ | WAS | CHI | STL | BUF | TB  | NO  | DET | ATL | SEA | SF  | 2  | CAR | IND | NYJ | NE  | CLE | PIT | BAL | CIN | TEN | MIA | OAK | HOU | NYG | DAL | JAC | PHI |
| STL | CAR | KC  | DET | PIT | WAS | CIN | CLE | MIA | NYG | ARZ | NE  | NO  | DAL | IND | JAC | 3  | NYJ | ATL | TB  | BUF | HOU | GB  | MIN | CHI | BAL | SF  | SEA | SD  | OAK | PHI | DEN | TEN |
| SD  | KC  | DEN | OAK | DET | CHI |     | PIT | NE  |     | MIA | ARZ | TB  | SF  | STL | HOU | 4  | BAL | NO  | ATL | TEN | BUF | CLE | CIN | MIN | SEA | JAC | IND | NYJ | PHI | NYG | WAS | DAL |
| DEN | PHI | NYG |     | NO  | GB  | DET |     | NYJ | ARZ | CHI |     | CAR | JAC | HOU | IND | 5  | CLE | BAL | CIN | ATL | MIA | NE  | BUF |     | SF  | SEA | STL | KC  | DAL | TEN | SD  | OAK |
| WAS | CHI | TB  | DAL | NYG | CLE | BAL | CAR |     | MIN | NE  | PHI | SF  | HOU | ARZ | TEN | 6  | CIN |     | NO  | PIT | GB  | BUF | DET | NYJ | STL | SD  | DEN | SEA | JAC | OAK | KC  | IND |
| PHI | MIN | DAL | CHI | WAS | CIN | CLE | NYG | TB  | STL |     | ATL | SEA | CAR | TEN | ARZ | 7  | MIA | BUF | NYJ | NE  | PIT | DET | GB  | BAL | KC  | DEN | SD  | SF  | IND | HOU |     | JAC |
| DET | PHI | NYG | DEN |     | DAL | MIN | GB  | ARZ | TB  | BUF | CAR | ATL | SEA | JAC | STL | 8  | NO  | NE  | MIA | CIN |     | NYJ | KC  | OAK |     |     | SF  |     | WAS | CLE | PIT |     |
| MIN |     | OAK | SD  | GB  |     | CHI | DAL | CAR | ATL | NYJ | SEA |     | TEN |     | TB  | 9  | KC  | CIN | PIT | NO  | CLE | MIA | BAL | NE  | IND | HOU |     | STL |     | BUF | PHI | WAS |
| NO  | OAK | GB  | MIN | DET | CHI | PHI | WAS | SEA | SF  | DAL | MIA | HOU | IND | CAR | ATL | 10 | PIT | TB  |     |     | CIN | BAL |     | BUF | ARZ | STL | TEN | JAC | SD  |     | NYG | DEN |
|     | GB  | WAS | PHI | BAL | PIT | NYG | SEA | TB  | NE  | SF  | ATL | JAC |     | NO  | MIN | 11 | NYJ | SD  | CAR | BUF | CHI | CLE | CIN | DET | OAK | TEN | ARZ | IND | KC  | DEN | HOU | MIA |
| NYG | DAL |     | SF  | STL | TB  | MIN | GB  | NO  | MIA | ATL | DET | IND | CHI | WAS |     | 12 |     | CAR | DEN | BAL | NYJ |     | PIT | CLE | JAC | ARZ | HOU | OAK | NE  | SD  | TEN | KC  |
| OAK | WAS | ARZ | NYG | MIN | GB  | DET | CHI | BUF | TB  | SEA | CAR | PHI | SF  | STL | NO  | 13 | ATL | NYJ | HOU | MIA | PIT | SD  | JAC | BAL | NE  | TEN | CLE | IND | KC  | DEN | DAL | CIN |
| CHI | SD  | DET | KC  | DAL | PHI | ATL | BAL | GB  | NO  | CAR | BUF | STL | ARZ | SEA | SF  | 14 | TB  | PIT | CLE | OAK | MIN | IND | NE  | MIA | JAC | CIN | HOU | DEN | TEN | WAS | NYJ | NYG |
| GB  | SEA | MIN | ATL | CLE | BAL | DAL | PHI | WAS | NYJ | STL | SF  | TEN | NO  | TB  | NYG | 15 | JAC | NE  | MIA | CAR | DET | PIT | CHI | CIN | IND | HOU | BUF | ARZ | SD  | OAK | KC  | DEN |
| WAS | DET | CHI | DAL | PHI | NYG | PIT | CIN | SF  | NO  | CAR | STL | SEA | TB  | ATL | ARZ | 16 | MIA | BUF | BAL | CLE | NE  | MIN | NYJ | GB  | DEN | KC  | TEN | JAC | HOU | IND | SD  | OAK |
| PHI | WAS | DAL | NYG | GB  | MIN | CHI | DET | CAR | ATL | TB  | NO  | SF  | SEA | ARZ | STL | 17 | NE  | NYJ | BUF | MIA | CIN | BAL | PIT | CLE | TEN | JAC | IND | HOU | OAK | SD  | DEN | KC  |

- NBC, CBS, FOX, ESPN, NFLN
- Shaded=home
- Left NFC (E, N, S, W), Right AFC (E, N, S, W)

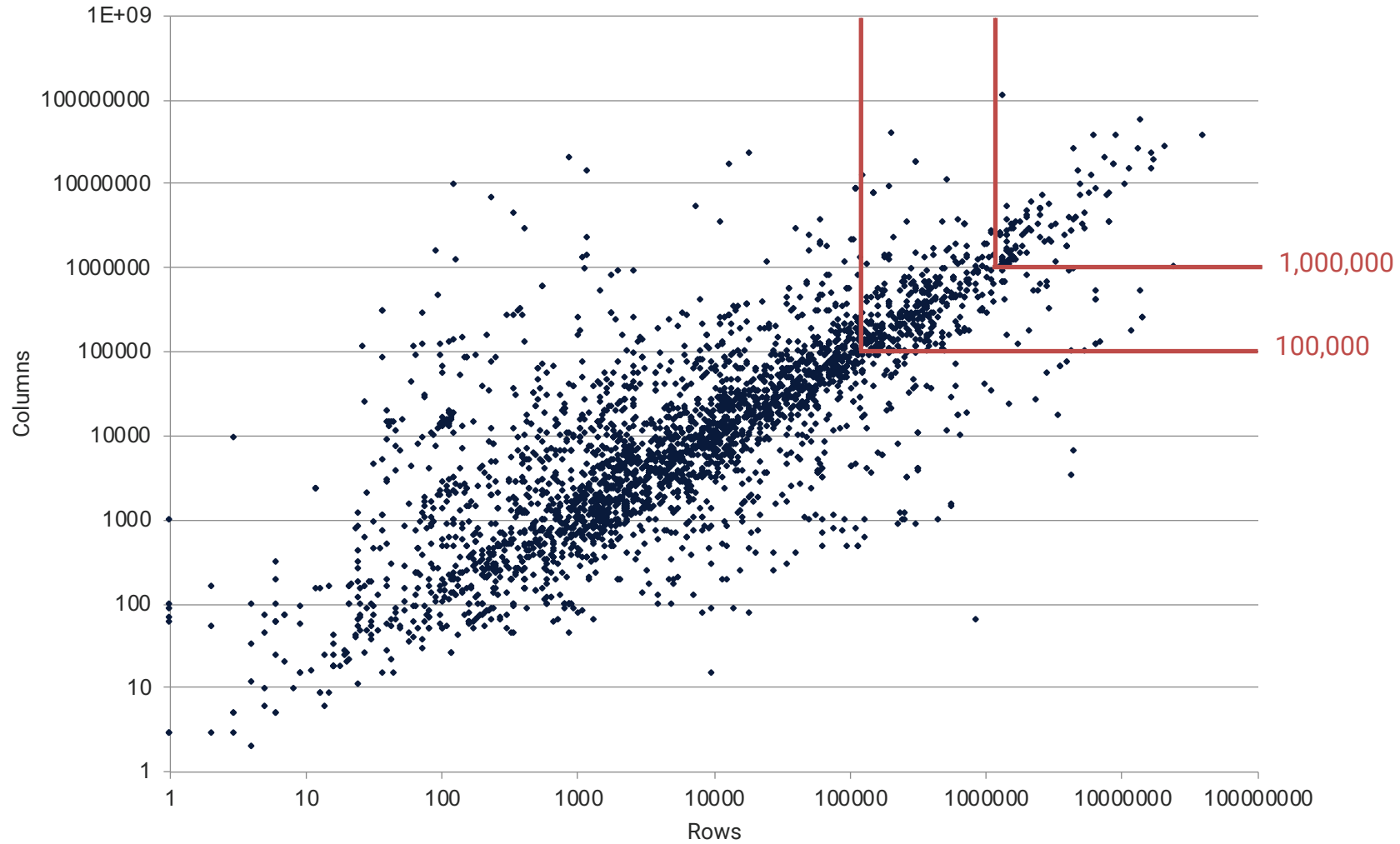
# Partial List of 2013 Rules and Goals



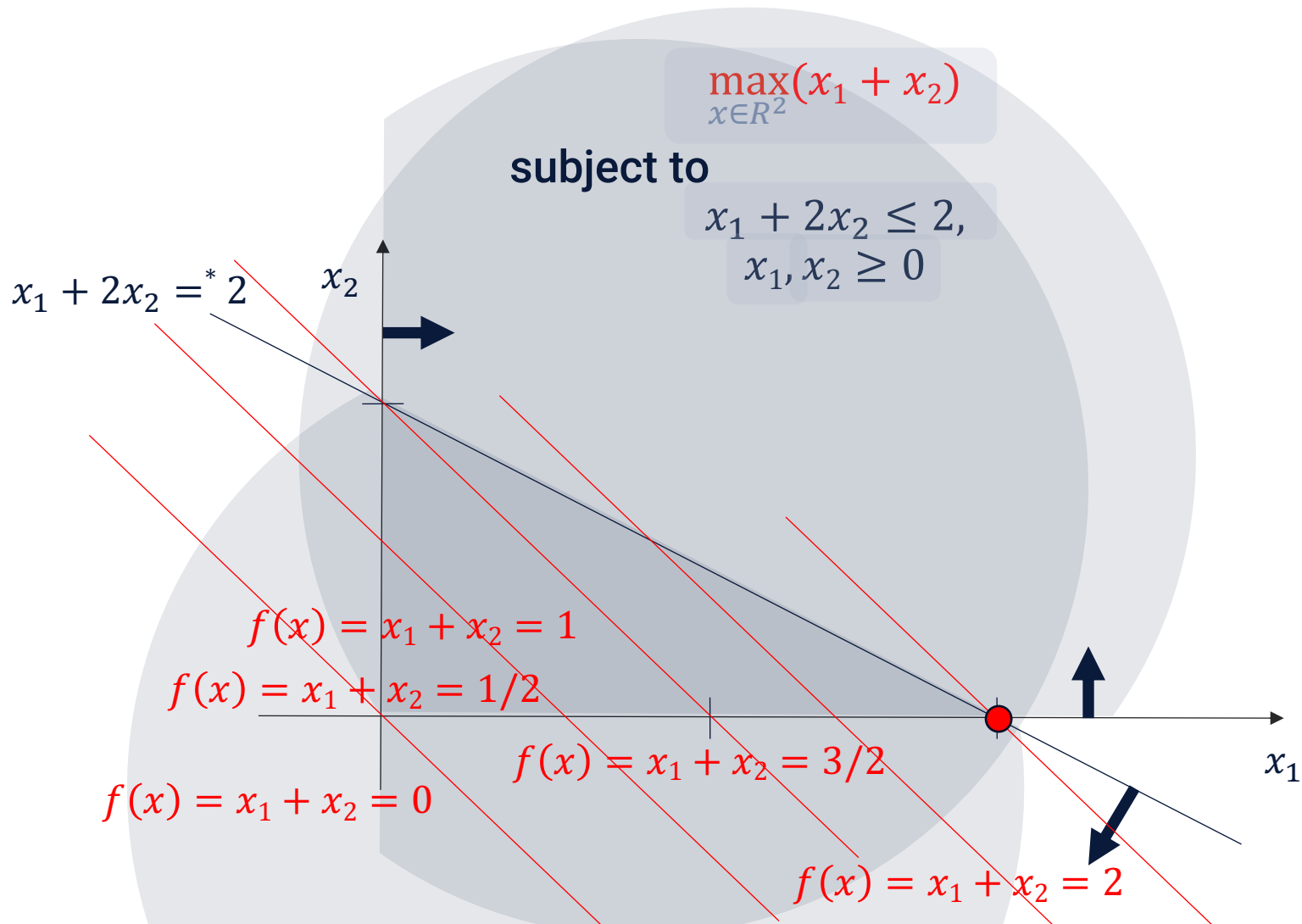
- Teams playing in London home week prior, on BYE week after
- Bills game in Toronto Week 13 against ATL, BAL, CAR, KC, MIA or NYJ
- No team has earliest BYE in consecutive seasons
- No team plays more than two road games against team coming off their BYE
- All teams playing road Thursday games are home the previous week
- Every team plays one Thursday game
- All teams playing home Thursday games have limited travel previous week
- Minimize non-division games during hurricane season (in order to “swap” sites)
- Minimize 3-game road trips (and 3-game home stands for teams with ticket issues)
- Minimize number of division series that end in first half of season
- Minimize number of games that would conflict with MLB postseason
- Maximize the number of late-season division games
- Minimize early-season games 1PM games for teams with weather concerns
- Minimize number of Pacific time zone teams that play at 1PM ET
- CBS/FOX have at least 3 1PM games every week, preferably geographically diverse
- CBS/FOX have at least 5 total games
- Team can play no more the 6 prime time games, and only 3 teams per year can play 6. All other teams can play no more than 5 primetime games (max 4 NBC)

# Gurobi MIP Library

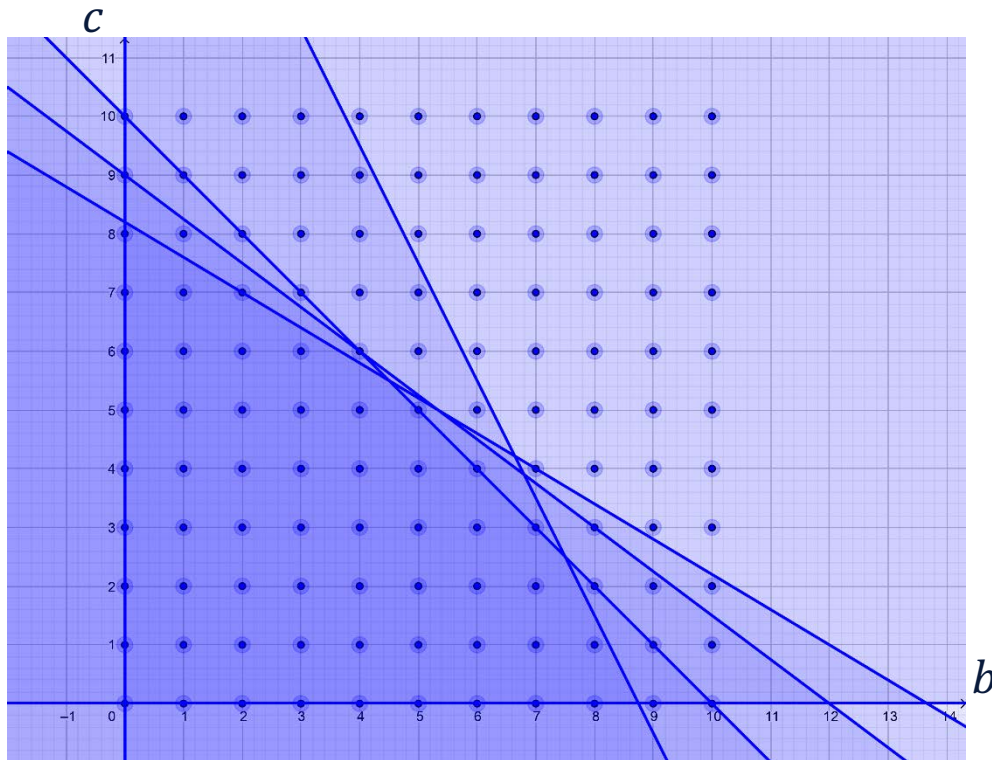
(5927 models)



# Linear Programming (LP) by Picture



# Mixed-Integer Programming (MIP) by Picture



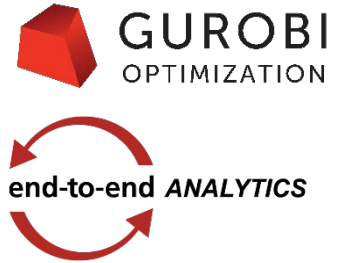
$$\begin{aligned} & \max_{b,c} (10b + 11c) \\ & \text{subject to} \\ & \quad b + c \leq 10, \\ & \quad 3b + 4c \leq 36, \\ & \quad 3b + 5c \leq 41, \\ & \quad 4b + 2c \leq 35, \\ & \quad b, c \geq 0 \end{aligned}$$

**Caveat:** although may look almost like an LP, algorithmically we are not that good at exploring the integer lattice,

- even a “simple” (0,1)-cube in n-dimensions would have  $2^n$  points! (for instance, in dimension 100 it would have  $\sim 1.26 \times 10^{30}$  points)

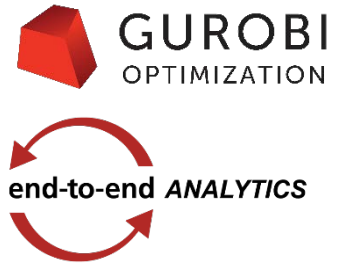
# Algorithms for Solving MP Problems

- Simplex (and dual simplex) method for LP
- Interior point algorithms for LP and QP
- Branch and bound for MIP
- Relaxation methods
- Heuristics
- Cutting planes
- Lazy constraints



# What Makes MIP Difficult?

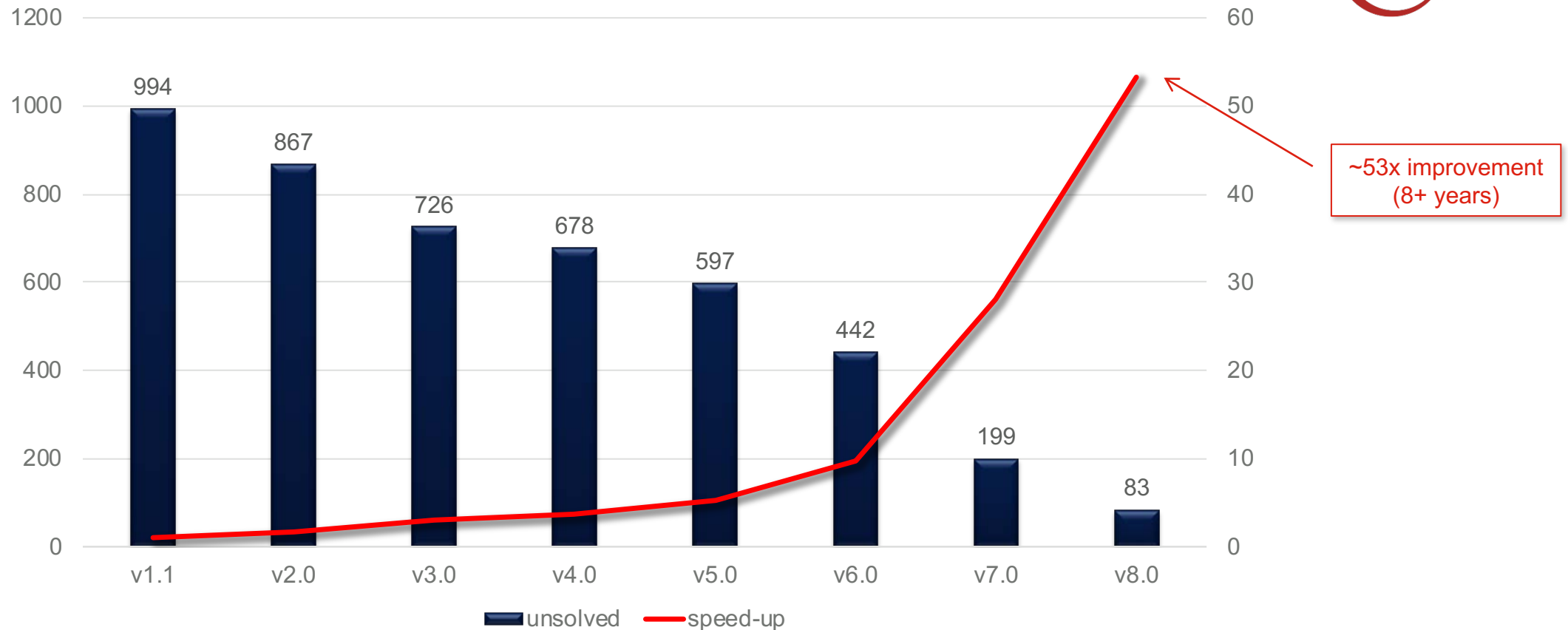
- LP vs MIP – polynomial vs NP-complete
- Numerical issues



# Importance of Solver Performance



## Comparison of Gurobi Versions (PAR-10)



~53x improvement  
(8+ years)

Time limit: 10000 sec.  
Intel Xeon CPU E3-1240 v3 @ 3.40GHz  
4 cores, 8 hyper-threads  
32 GB RAM

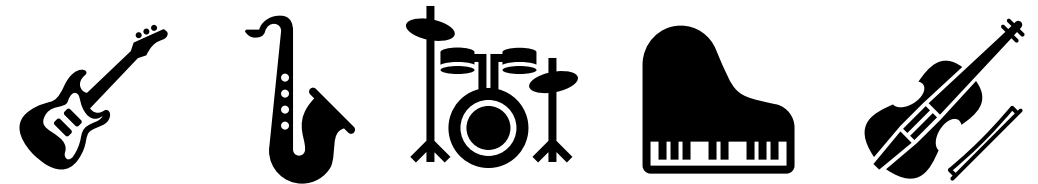
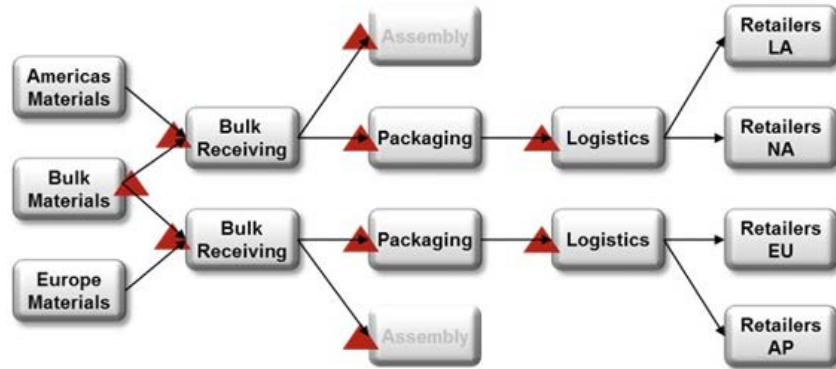
Test set has 5656 models:  
- 410 discarded due to inconsistent answers  
- 1493 discarded that none of the versions can solve  
- speed-up measured on >100s bracket: 2012 models



# Identifying Optimization Problems Within Your Organization

Dr. Russell Halper

# When Does Optimality Matter?



## Designing a Distribution Network

**Challenge:** Where do I put my assets and how do I move products between them?

**Decision:** A selection of sites to build assets, type of asset, and a flow of products to/from each

**Cost of a Single Sub-Optimal Decision:** Often times, tens of millions of dollars... or more!

## Music Recommendation

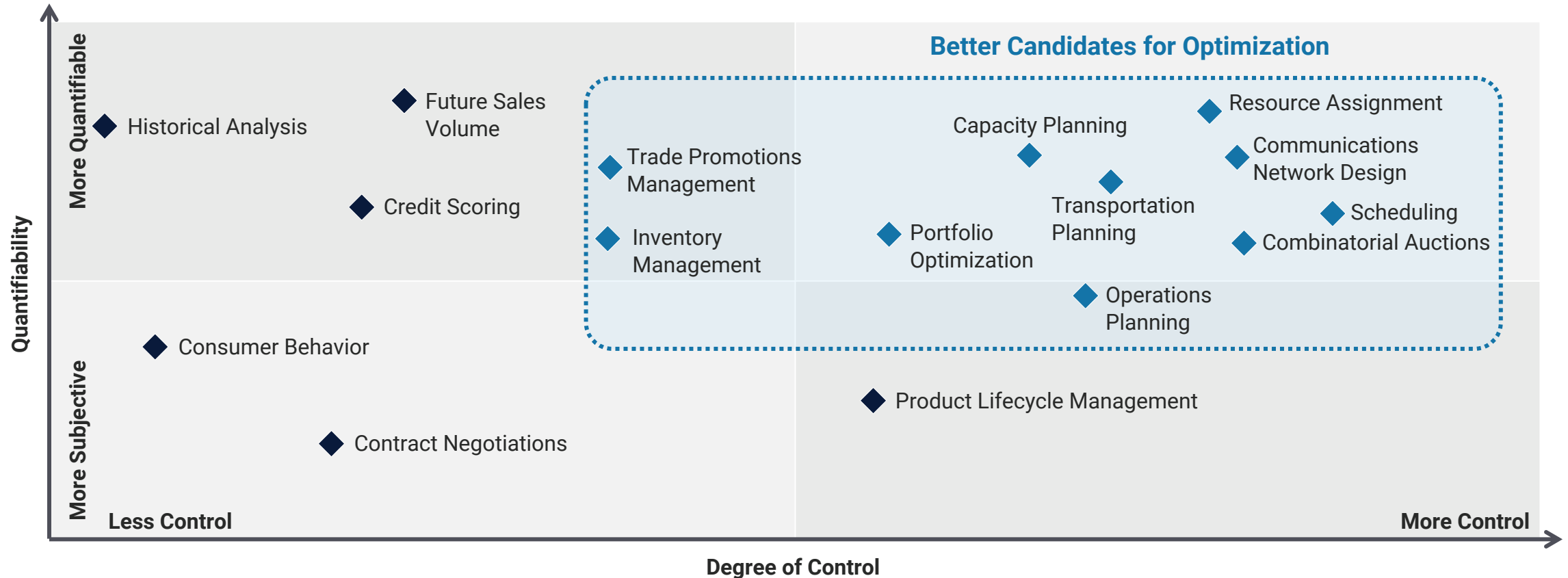
**Challenge:** What songs would a customer enjoy?

**Decision:** A selection of one or more songs to play to a customer

**Cost of a Single Sub-Optimal Decision:** Negligible

# Identifying Opportunities for Optimization

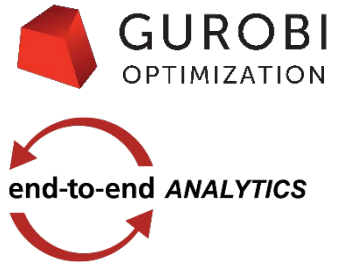
Optimization can often be used when the business has a high degree of control over a reasonably quantifiable business problem.



# How MIP Complements Machine Learning

Dr. Russell Halper

# Many ML Techniques Use *Some* Type of Optimization



| PREDICTING A VALUE   |  |   |  | SEGMENTING  |  |
|--|--|---|--|---|--|
| Predict a numerical value  |  | Predict a categorical value   |  | Group together like data  |  |
| Is the predicted value linear in the data?   |  | Is the predicted value linear in the data?  |  | Is the number of groups known?  |  |
| Linear Methods   | Nonlinear Methods  | Linear Methods  | Nonlinear Methods  | Known   | Unknown  |
| <p><b>Linear Regression</b></p> <p>Prior knowledge and/or small data sets: <b>Bayesian Linear Regression</b></p> <p>Feature reduction: <b>LASSO, Ridge</b></p> | <p>Interpretability: <b>Regression Trees</b></p> <p>Accuracy: <b>Random Forests</b></p> <p>Large data sets: <b>Neural Network Regression</b></p> | <p>Probabilistic Approach: <b>Logistic Regression</b></p> <p>Explicitly create boundaries: <b>Support Vector Machines</b></p> | <p>Interpretability: <b>Classification Trees</b></p> <p>Accuracy: <b>Random Forests</b></p> <p>Large data sets: <b>Neural Network Classification</b></p> | <p>Each data point in its own cluster: <b>K-Means, K-Median</b></p> <p>Overlapping clusters: <b>EM Clustering</b></p> | <p>Always gives the same result: <b>Hierarchical clustering</b></p> <p><b>Affinity Propagation</b></p> |

# Many ML Techniques Use *Some* Type of Optimization

| PREDICTING A VALUE  |   |  |   | SEGMENTING   |   |
|---|---|--|---|--|---|
| Predict a numerical value<br>Is the predicted value linear in the data?   |   | Predict a categorical value<br>Is the predicted value linear in the data?  |   | Group together like data<br>Is the number of groups known?   |   |
| Linear Methods  | Nonlinear Methods   | Linear Methods   | Nonlinear Methods   | Known  | Unknown   |
| <b>Linear Regression</b><br><br>Prior knowledge and/or small data sets: <b>Bayesian Linear Regression</b><br><br>Feature reduction: <b>LASSO, Ridge</b> | Interpretability: <b>Regression Trees</b><br><br>Accuracy: <b>Random Forests</b><br><br>Large data sets: <b>Neural Network Regression</b> | Probabilistic Approach: <b>Logistic Regression</b><br><br>Explicitly create boundaries: <b>Support Vector Machines</b> | Interpretability: <b>Classification Trees</b><br><br>Accuracy: <b>Random Forests</b><br><br>Large data sets: <b>Neural Network Classification</b> | Each data point in its own cluster: <b>K-Means, K-Median</b><br><br>Overlapping clusters: <b>EM Clustering</b> | Always gives the same result: <b>Hierarchical clustering</b><br><br><b>Affinity Propagation</b> |



## Regression

Minimize the sum of squared errors when fitting the model

## Neural Networks

Stochastic Gradient Descent is used to minimize the average error over the training data set

## K-Median/K-Means

Assign a data point to a cluster to minimize some aggregate distance metric

# K-Median Clustering as a MIP

From a set  $P$  of data points, select a subset of  $k$  points (i.e., “centers”) that minimizes the distance from each point in  $P$  to its closest center

## Index Sets

$P$  = the set of points in the model

## Data

$Dist_{ij}$  = Distance between points  $i$  and  $j$

## Variables

$$y_j = \begin{cases} 1 & \text{if point } j \text{ is a Center} \\ 0 & \text{otherwise} \end{cases}$$
$$x_{ij} = \begin{cases} 1 & \text{if point } i \text{ is assigned to center } j \\ 0 & \text{otherwise} \end{cases}$$

Minimize:  $\sum_{i,j \in P} Dist_{ij} x_{ij}$     Minimize the Distance

Subject To:

$$\sum_{j \in P} y_j = k$$
    Select  $k$  centers
$$x_{ij} \leq y_j \text{ for all } i, j \in P$$
    Only assign points to a selected center
$$\sum_{j \in P} x_{ij} = 1 \text{ for all } i \in P$$
    Each point must be assigned to exactly one center
$$x_{ij}, y_j \in \{0,1\} \text{ for all } i, j \in P$$
    Variables are either 0 or 1

# Predictive Models Often Require Actions to Be Taken Before Value is Realized....



**Descriptive**

What happened and why?

**Predictive**

What will happen and why?

**Prescriptive**

What should the organization do?

## Predictive ML

Many excellent options!

### Interpretable:

- Lasso
- Random Forests
- Classification Trees

### Non-Interpretable:

- Neural Networks
- Reservoir Computing

## Prescriptive

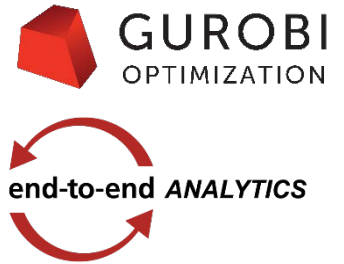
- **Mathematical Programming (Optimization):** Provably optimal results. High degree of control over problem.
- **AI/Neural Networks:** Evolving technology and useful for many problems. Black box.
- **Simulation:** Useful for non-convex problems with multiple local minima or highly-linear problems
- **Heuristics:** Obtainable but can be inflexible when new constraints added to a business problem

Provably optimal solution

Generally not provably optimal solutions



# Should I Use MIP, AI, or Another Approach?



- How important is optimality?
  - Is the cost of sub-optimal solutions high?
  - Most optimization models are NP-Complete problems. Polynomial runtime algorithms cannot find an optimal solution.
  
- Does data exist to train a model? Is it a new situation? Will the business problem change?
  
- What type of scenarios analysis needs to be done? What type of sensitivity analysis needs to be done?
  
- Do I need more than one solution?
  
- How big is the problem?

# Optimization and Machine Learning Working Together

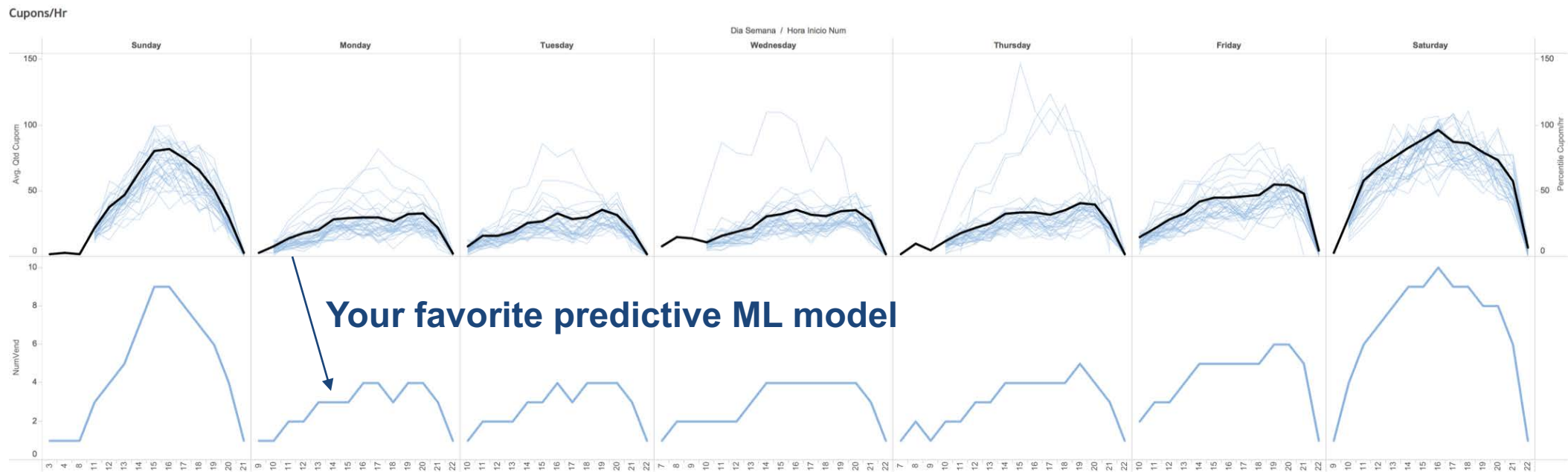
- Retail chain w/ ~200 stores
- +1400 Employees
- Demand varies throughout the day
- Complicated local labor laws
- Problem statement: How much staff should we hire for each store?

|           | 1-Monday | 2-Tuesday | 3-Wednesday | 4-Thursday | 5-Friday | 6-Saturday | 7-Sunday | 1-Monday | 2-Tuesday | 3-Wednesday | 4-Thursday | 5-Friday | 6-Saturday | 7-Sunday | 1-Monday | 2-Tuesday | 3-Wednesday | 4-Thursday | 5-Friday | 6-Saturday | 7-Sunday |   |
|-----------|----------|-----------|-------------|------------|----------|------------|----------|----------|-----------|-------------|------------|----------|------------|----------|----------|-----------|-------------|------------|----------|------------|----------|---|
| 1048.1.1  |          | 8         | 8           | 8          |          | 10         | 8        |          | 8         | 8           |            | 8        | 8          | 8        | 8        | 8         |             |            |          |            | 8        |   |
| 1048.1.13 |          |           |             | 8          | 8        | 10         | 8        |          | 8         |             |            |          | 8          |          |          |           |             | 8          | 8        | 10         | 8        |   |
| 1048.1.18 |          |           |             |            |          | 10         | 8        |          | 8         | 8           |            |          | 10         |          |          | 8         | 8           | 8          |          | 8          | 8        |   |
| 1048.1.2  |          |           | 8           | 8          | 8        | 8          | 8        |          |           | 8           | 8          |          | 10         | 8        | 8        |           | 8           | 8          | 8        | 8          | 8        |   |
| 1048.1.21 | 8        | 8         |             |            | 8        | 10         |          | 8        |           | 8           | 8          |          | 8          | 8        |          | 8         | 8           | 8          |          | 8          | 8        |   |
| 1048.1.26 | 8        |           |             | 8          | 8        | 8          | 8        |          |           |             |            | 8        | 10         | 8        |          |           |             |            | 8        | 8          |          |   |
| 1048.1.29 | 8        | 8         |             |            | 8        | 8          | 8        | 8        | 8         |             | 8          | 8        | 8          |          |          | 8         |             | 8          | 8        | 10         | 8        |   |
| 1048.1.3  |          |           |             |            | 8        | 8          |          | 8        | 8         |             |            | 8        | 10         | 8        |          |           |             | 8          | 8        | 8          | 8        | 8 |
| 1048.1.31 | 8        |           | 8           | 8          | 8        | 8          | 8        | 8        |           | 8           | 8          | 8        | 10         |          | 8        |           | 8           | 8          | 8        | 8          | 8        | 8 |
| 1048.1.35 |          | 8         | 8           | 8          |          | 8          | 8        |          |           | 8           | 8          | 8        | 10         | 8        | 8        |           |             | 8          | 8        | 8          |          |   |
| 1048.1.38 | 8        | 8         |             |            | 8        | 8          |          |          |           |             |            | 8        | 10         | 8        |          | 8         |             | 8          |          | 10         | 8        |   |
| 1048.1.39 | 8        | 8         |             | 8          |          | 8          | 8        |          | 8         |             | 8          | 8        | 10         |          | 8        | 8         |             | 8          | 8        | 8          | 8        | 8 |
| 1048.1.4  | 8        | 8         | 8           |            | 8        | 10         | 8        | 8        | 8         |             | 8          | 8        | 8          | 8        | 8        |           | 8           | 8          | 8        | 10         |          |   |
| 1048.1.42 |          |           | 8           | 8          | 8        | 8          | 8        |          | 8         | 8           | 8          |          | 8          |          | 8        | 8         |             |            | 8        | 10         | 8        |   |
| 1048.1.44 |          |           |             |            |          | 10         |          | 8        | 8         |             | 8          | 8        | 8          | 8        |          |           |             |            | 8        | 8          | 8        | 8 |
| 1048.1.5  |          | 8         | 8           |            | 8        | 10         |          |          |           |             |            |          | 8          | 8        |          | 8         |             |            | 8        | 10         | 8        |   |
| 1048.1.6  | 8        |           | 8           | 8          | 8        | 8          | 8        | 8        |           | 8           | 8          |          | 10         | 8        | 8        | 8         | 8           |            | 8        | 10         |          |   |
| 1048.1.7  |          | 8         | 8           | 8          | 8        | 10         |          | 8        |           | 8           | 8          | 8        | 8          | 8        |          | 8         | 8           | 8          | 8        | 10         | 8        |   |

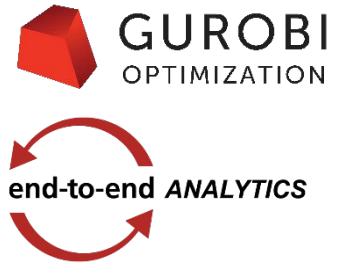
# Developing a Predictive Model

So how does one predict how much labor is needed?

- Register sales provided a key piece of data that help to understand the level of staffing over time.
- Other key demand drivers: Day of week, Time of Day, Holidays, Seasonality, Weather, ....
- What does the business need out of a predictive model:



# What Does the Optimization Model need to Consider?



**Determine how many employees to hire (minimize)**

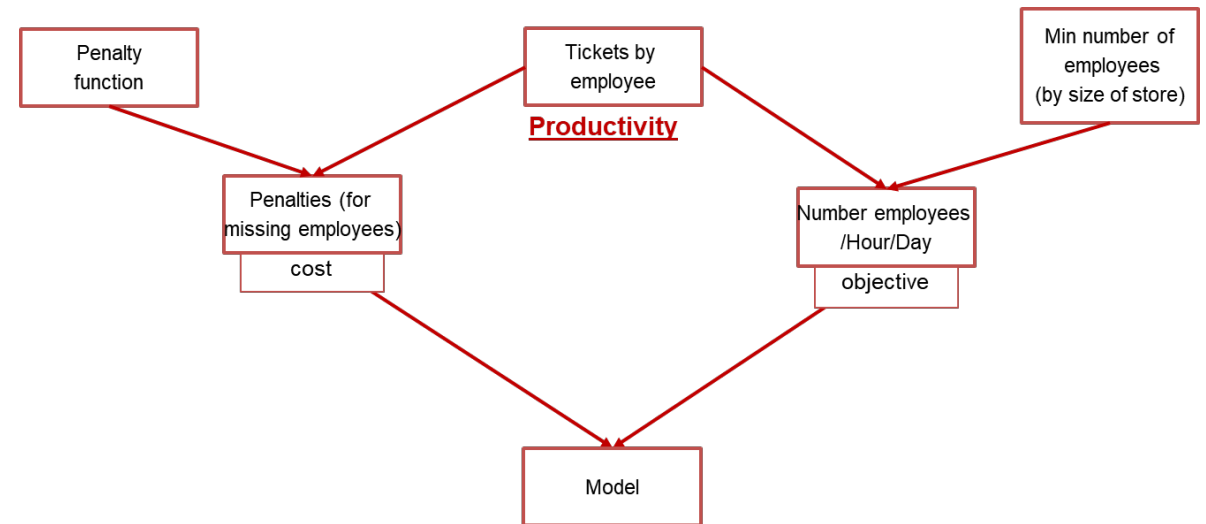
**Schedule (what days, what hours, when to break)**

**Employees are of 2 types:**

- Regular employees
  - Fixed monthly salary
  - Can be scheduled at most 6 consecutive days
  - Can be scheduled at most 2 consecutive Sundays
  - Same starting hour during weekdays
  - Fixed number of hours per day (9 hours)
  - Overtime is available (at additional cost)
  - Min and max number of hours per week
  - During a day, cannot work more than 6 hours without a 1-hour break\
- Part-time employees
  - Salary determined by assigned hours
  - Less restrictions of consecutive days or Sundays
  - Flexible starting hours
  - No overtime is available

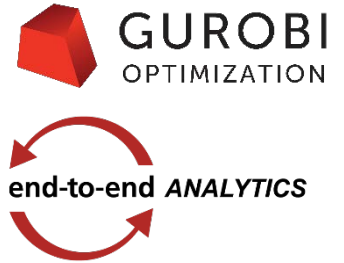
## Model Penalties

- The model penalizes if there are fewer employees assigned than the requirement (by hour, day)
- It is assumed that fewer employees will result in loss of sales



$$\text{Total Cost} = \text{Salaries} + \text{Penalties} + \text{Overtime costs}$$

# Resources



- Access [www.gurobi.com](http://www.gurobi.com) and browse through Resources on our website
  - This includes code examples, webinar recordings, documentation and information on how to get started with optimization.
- Get a free 30-day trial of Gurobi
  - [www.gurobi.com/eval](http://www.gurobi.com/eval)
- Join us in next week's webinar (May 21 & 22):
  - Optimization Application Demos - This presentation will walk through two live demos implemented by the Gurobi team and deployed on Amazon Web Services using Docker and Gurobi Instant Cloud.
  - Register now: <https://bit.ly/2LshNki>
- Need help leveraging Optimization for your business?
  - Contact [russell@e2eanalytics.com](mailto:russell@e2eanalytics.com).