Model-Based Optimization
+ Application Programming
= Streamlined Deployment in AMPL

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Examples

Model-based optimization

- Model-based vs. Method-based *approaches*
  - Example: Balanced assignment
- Declarative vs. Executable *modeling languages*
  - Example: AMPL vs. gurobipy for multicommodity flow

Examples

Model-based optimization

Application programming

- Extending a modeling language with scripting
  - Example: Tradeoffs between roll-cutting objectives

Examples

Model-based optimization

Application programming

Streamlined deployment

- Modeling language APIs
  - Example: Pattern enumeration in Python and R
- Python integration
  - Example: Python data embedded in an AMPL model
  - Example: Custom stopping criteria using Gurobi callbacks
  - Example: Executing Python inside AMPL
- AMPL in Jupyter notebooks
  - Example: Mixed AMPL and Python notebooks
- Building a decision-making tool for deployment
  - Example: QuanDec

Model-Based vs. Method-Based Approaches to Optimization

Example: ***Balanced Assignment***

- meeting of employees from around the world

Given

- several employee categories
  (title, location, department, male/female)
- a specified number of project groups

Assign

- each employee to a project group

So that

- the groups have about the same size
- *the groups are as "diverse" as possible* with respect to all categories

Method-Based Approach

Define an algorithm to build a balanced assignment

- Start with all groups empty
- Make a list of people (employees)
- For each person in the list:
  - Add to the group whose resulting "sameness" will be least

```
Initialize all groups G = { }

Repeat for each person p
   sMin = Infinity

   Repeat for each group G
      s = total "sameness" in G ∪ {p}

      if s < sMin then
         sMin = s
         GMin = G

   Assign person p to group GMin
```

Method-Based Approach *(cont'd)*

Define a computable concept of "sameness"

- Sameness of any two people:
  - Number of categories in which they are the same
- Sameness of a group:
  - Sum of the sameness of all pairs of people in the group

Refine the algorithm to get better results

- Reorder the list of people
- Locally improve the initial "greedy" solution by swapping group members
- Seek further improvement through local search metaheuristics
  - What are the neighbors of an assignment?
  - How can two assignments combine to create a better one?

Model-Based Approach

Formulate a "minimal sameness" model

- Define decision variables for assignment of people to groups
  - $x_{ij} = 1$ if person 1 assigned to group j
  - $x_{ij} = 0$ otherwise
- Specify valid assignments through constraints on the variables
- Formulate sameness as an objective to be minimized
  - *Total sameness* = sum of the sameness of all groups

Send to an off-the-shelf solver

- Choice of excellent solvers
- Broad problem classes handled efficiently
- Special cases recognized and exploited to advantage
  - zero-one variables like x_{ij}

Model-Based Formulation

Given

P set of people

C set of categories of people

t_{ik} type of person i within category k, for all $i \in P, k \in C$

and

G number of groups

$g^{\min}$ lower limit on people in a group

$g^{\max}$ upper limit on people in a group

Define

$s_{i_1 i_2} = |\{k \in C\colon\ t_{i_1 k} = t_{i_2 k}\}|$, for all $i_1 \in P, i_2 \in P$

sameness of persons i_1 and i_2

Model-Based Formulation *(cont'd)*

Determine

$x_{ij} \in \{0,1\}$ $= 1$ if person i is assigned to group j
$= 0$ otherwise, for all $i \in P$, $j = 1, \ldots, G$

To minimize

$\sum_{i_1 \in P} \sum_{i_2 \in P} s_{i_1 i_2} \sum_{j=1}^{G} x_{i_1 j}\, x_{i_2 j}$

total sameness of all pairs of people in all groups

Subject to

$\sum_{j=1}^{G} x_{ij} = 1,$ for each $i \in P$

each person must be assigned to one group

$g^{\min} \leq \sum_{i \in P} x_{ij} \leq g^{\max}$, for each $j = 1, \ldots, G$

each group must be assigned an acceptable number of people

Model-Based Solution

Optimize with an off-the-shelf solver

Choose among many alternatives

- Linearize and send to a mixed-integer linear solver
  - CPLEX, Gurobi, Xpress; CBC, MIPCL, SCIP
- Send quadratic formulation to a mixed-integer solver that automatically linearizes products involving binary variables
  - CPLEX, Gurobi, Xpress
- Send quadratic formulation to a nonlinear solver
  - Mixed-integer nonlinear: Knitro, BARON
  - Continuous nonlinear (might come out integer): MINOS, Ipopt, . . .

Model-Based vs. Method-Based

Where is the work?

- *Method-based:* Programming an implementation of the method
- *Model-based:* Constructing a formulation of the model

Which should you prefer?

- For simple problems, any approach can seem pretty easy
- *But real optimization problems are seldom simple . . .*

Complications in Balanced Assignment

"Total Sameness" is problematical

- ❖ Hard for client to relate to goal of diversity
- ❖ *Minimize "total variation" instead*
  - ∗ Sum over all types: most minus least assigned to any group

Client has special requirements

- ❖ No employee should be "isolated" within their group
  - ∗ No group can have exactly one woman
  - ∗ Every person must have a group-mate
    from the same location and of equal or adjacent rank

Room capacities are variable

- ❖ Different groups have different size limits
- ❖ *Minimize "total deviation"*
  - ∗ Sum over all types: greatest violation of target range for any group

Method-Based *(cont'd)*

Revise or replace the solution approach

- Total variation is less suitable to a greedy algorithm
- Total variation is harder to locally improve
- Client constraints are challenging to enforce

Update or re-implement the method

- Even small changes to the problem can necessitate major changes to the method and its implementation

Balanced Assignment

Model-Based *(cont'd)*

Replace the objective

Formulate additional constraints

Send back to the solver

Model-Based *(cont'd)*

To write new objective, add variables

$y_{kl}^{\min}$ fewest people of category k, type l in any group,

$y_{kl}^{\max}$ most people of category k, type l in any group,

for each $k \in C, l \in T_k = \bigcup_{i \in P} \{t_{ik}\}$

Add defining constraints

$y_{kl}^{\min} \leq \sum_{i \in P: t_{ik} = l} x_{ij}$, for each $j = 1, \ldots, G;\ k \in C, l \in T_k$

$y_{kl}^{\max} \geq \sum_{i \in P: t_{ik} = l} x_{ij}$, for each $j = 1, \ldots, G;\ k \in C, l \in T_k$

Minimize total variation

$\sum_{k \in C} \sum_{l \in T_k} (y_{kl}^{\max} - y_{kl}^{\min})$

Model-Based *(cont'd)*

To express client requirement for women in a group, let

$$Q = \{i \in P: t_{i,\mathrm{m/f}} = \text{female}\}$$

Add constraints

$$\textstyle\sum_{i \in Q} x_{ij} = 0 \ \text{ or } \ \sum_{i \in Q} x_{ij} \geq 2, \ \text{for each } j = 1, \ldots, G$$

Model-Based *(cont'd)*

To express client requirement for women in a group, let

$$Q = \{i \in P\colon t_{i,\mathrm{m/f}} = \text{female}\}$$

Define logic variables

$$z_j \in \{0,1\} = 1 \text{ if any women assigned to group } j$$
$$= 0 \text{ otherwise, for all } j = 1, \ldots, G$$

Add constraints relating
logic variables to assignment variables

$$z_j = 0 \Rightarrow \sum_{i \in Q} x_{ij} = 0,$$

$$z_j = 1 \Rightarrow \sum_{i \in Q} x_{ij} \geq 2\,, \text{ for each } j = 1, \ldots, G$$

Model-Based *(cont'd)*

To express client requirement for women in a group, let

$$Q = \{i \in P \colon t_{i,\mathrm{m/f}} = \text{female}\}$$

Define logic variables

$$z_j \in \{0,1\} = 1 \text{ if any women assigned to group } j$$
$$= 0 \text{ otherwise, for all } j = 1, \ldots, G$$

Linearize constraints relating logic variables to assignment variables

$$2z_j \leq \sum_{i \in Q} x_{ij} \leq |Q|\, z_j, \text{ for each } j = 1, \ldots, G$$

Method-Based Remains Popular for . . .

Heuristic approaches

- ❖ Simple heuristics
  - ∗ Greedy algorithms, local improvement methods
- ❖ Metaheuristics
  - ∗ Evolutionary methods, simulated annealing, tabu search, GRASP, . . .

Situations hard to formulate mathematically

- ❖ Difficult combinatorial constraints
- ❖ Black-box objectives and constraints

Large-scale, intensive applications

- ❖ Routing fleets of delivery trucks
- ❖ Finding shortest routes in mapping apps

. . . and it appeals to programmers

Model-Based Has Become Common for . . .

Diverse application areas *(active AMPL users)*

- Energy and Utilities
  - power networks, gas pipelines, hydroelectric power, water distribution
- Industry
  - mining, steel, chemicals, oil refining, forestry and paper
  - cars & trucks, paper products, processed foods
- Transportation
  - airlines, trucking
- Services
  - supply chain, hospitals & medicine, construction management
- Communications
  - telecommunications, social media, cloud computing, distribution
- Finance
  - software tools, investment management, commodity management
- Advanced Technologies
  - artificial intelligence, distributed computing, biotechnology

Model-Based Has Become Common for . . .

Diverse application areas

Diverse fields

- Operations research & management science
- Business analytics
- Engineering & science
- Economics & finance

Model-Based Has Become Common for . . .

Diverse industries

Diverse fields

Diverse kinds of users

- Anyone who took an "optimization" class
- Anyone else with a technical background
- Newcomers to optimization

These have in common . . .

- Users inclined toward modeling; focus is
  - more on *what* should be solved
  - less on *how* it should be solved
- Good algebraic formulations for off-the-shelf solvers

Trends Favor Model-Based Optimization

Model-based approaches have spread

- Model-based metaheuristics ("Matheuristics")
- Solvers for SAT, planning, constraint programing

Off-the-shelf optimization solvers have kept improving

- Solve the same problems faster and faster
- Handle broader problem classes
- Recognize special cases automatically

Optimization models have become easier to embed within broader methods

- Model-based evolution of solver APIs
- APIs for optimization modeling systems

Modeling Languages for Model-Based Optimization

Background

- The modeling lifecycle
- Modeling languages
- Algebraic modeling languages

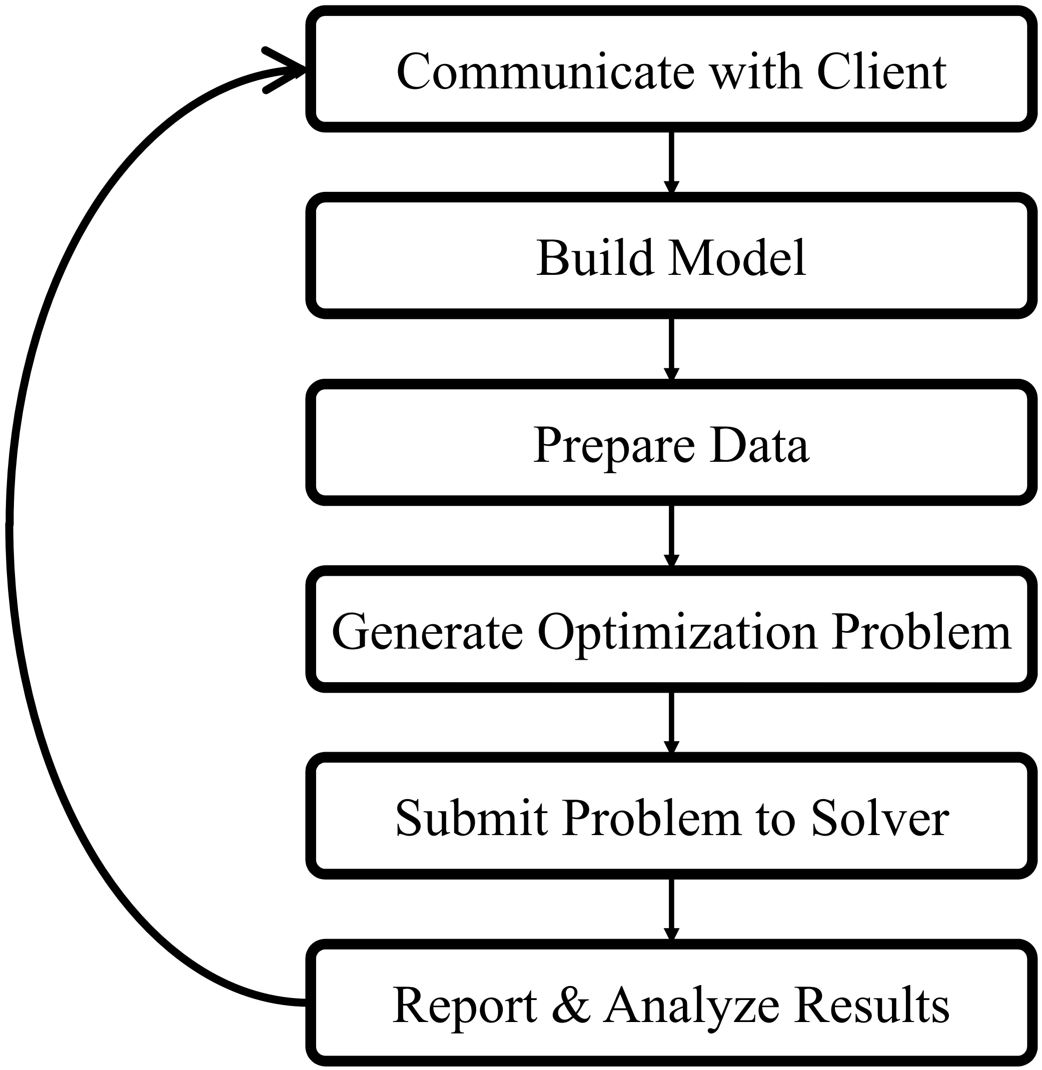
Design approaches

- Matrix generators vs. modeling languages
- Declarative vs. executable modeling languages

Example: AMPL vs. gurobipy

Example: Balanced Assignment in AMPL

The Optimization Modeling Lifecycle



Managing the Modeling Lifecycle

Goals for optimization software

- Repeat the cycle quickly and reliably
- Get results before client loses interest
- Deploy for application

Complication: two forms of an optimization problem

- Modeler's form
  - Mathematical description, easy for people to work with
- Solver's form
  - Explicit data structure, easy for solvers to compute with

Challenge: translate between these two forms

Modeling Languages

Describe your model

- Write your symbolic model in a *computer-readable modeler's form*
- Prepare data for the model
- Let computer translate to & from the solver's form

Limited drawbacks

- Separate language to be learned
- Overhead in translation to algorithm's form
- Confidential formulation to be protected

Great advantages

- Faster modeling cycles
- More reliable modeling
- More maintainable applications

Algebraic Modeling Languages

Designed for a model-based approach

- Define data in terms of sets & parameters
  - Analogous to database keys & records
- Define decision variables
- Minimize or maximize an algebraic function of decision variables
- Subject to algebraic equations or inequalities that constrain the values of the variables

Advantages

- Familiar
- Powerful
- Proven

AMPL

Algebraic modeling language and system

- Built specially for optimization
- Designed to support many solvers

Design goals

- Powerful, general expressions
- Natural, easy-to-learn modeling principles
- Efficient processing that scales well with problem size

Executable vs. Declarative Modeling Languages for Optimization

Example: *Two representative widely used systems*

Executable: *gurobipy*

- Python modeling interface for Gurobi solver
- http://gurobi.com

Declarative: AMPL

- Specialized modeling language with multi-solver support
- http://ampl.com

Executable

Concept

- Create an algebraic modeling language
  inside a general-purpose programming language
- Redefine operators like + and <=
  to return constraint objects rather than simple values

Advantages

- Ready integration with applications
- Good access to advanced solver features

Disadvantages

- Programming issues complicate description of the model
- Modeling and programming bugs are hard to separate
- Efficiency issues are more of a concern

Declarative

Concept

- Design a language specifically for optimization modeling
  - Resembles mathematical notation as much as possible
- Extend to command scripts and database links
- Connect to external applications via APIs

Disadvantages

- Adds a system between application and solver
- Does not have a full object-oriented programming framework

Advantages

- Streamlines model development
- Promotes validation and maintenance of models
- Can provide APIs for many popular programming languages

Comparison: Executable vs. Declarative

Example: Multicommodity Flow

- ship multiple goods over a network

Given

- networks nodes and arc
- supplies or demands at the nodes
- capacities on the arcs

Determine

- how much to ship over each arc

So that

- demands are met by the supplies
- *shipping costs are minimized*

Comparison

Data

gurobipy

- Assign values to Python lists and dictionaries

```
commodities = ['Pencils', 'Pens']

nodes = ['Detroit', 'Denver',
 'Boston', 'New York', 'Seattle']

arcs, capacity = multidict({
 ('Detroit', 'Boston'):   100,
 ('Detroit', 'New York'):  80,
 ('Detroit', 'Seattle'):  120,
 ('Denver',  'Boston'):   120,
 ('Denver',  'New York'): 120,
 ('Denver',  'Seattle'):  120 })
```

- Provide data later in a separate file →

AMPL

- Define symbolic model sets and parameters

```
set COMMODITIES;
set NODES;

set ARCS within {NODES,NODES};
param capacity {ARCS} >= 0;
```

```
set COMMODITIES := Pencils Pens ;

set NODES := Detroit Denver
 Boston 'New York' Seattle ;

param: ARCS: capacity:
        Boston 'New York' Seattle :=
 Detroit    100        80      120
 Denver     120       120      120  ;
```

Comparison

Data *(cont'd)*

gurobipy

```
inflow = {
 ('Pencils', 'Detroit'):   50,
 ('Pencils', 'Denver'):    60,
 ('Pencils', 'Boston'):   -50,
 ('Pencils', 'New York'): -50,
 ('Pencils', 'Seattle'):  -10,
 ('Pens',    'Detroit'):   60,
 ('Pens',    'Denver'):    40,
 ('Pens',    'Boston'):   -40,
 ('Pens',    'New York'): -30,
 ('Pens',    'Seattle'):  -30 }
```

AMPL

```
param inflow {COMMODITIES,NODES};
```

```
param inflow (tr):
              Pencils  Pens :=
  Detroit        50     60
  Denver         60     40
  Boston        -50    -40
 'New York'     -50    -30
  Seattle       -10    -30   ;
```

Comparison

Data *(cont'd)*

gurobipy

```
cost = {
  ('Pencils', 'Detroit', 'Boston'):   10,
  ('Pencils', 'Detroit', 'New York'): 20,
  ('Pencils', 'Detroit', 'Seattle'):  60,
  ('Pencils', 'Denver',  'Boston'):   40,
  ('Pencils', 'Denver',  'New York'): 40,
  ('Pencils', 'Denver',  'Seattle'):  30,
  ('Pens',    'Detroit', 'Boston'):   20,
  ('Pens',    'Detroit', 'New York'): 20,
  ('Pens',    'Detroit', 'Seattle'):  80,
  ('Pens',    'Denver',  'Boston'):   60,
  ('Pens',    'Denver',  'New York'): 70,
  ('Pens',    'Denver',  'Seattle'):  30 }
```

Comparison

Data *(cont'd)*

AMPL

```
param cost {COMMODITIES,ARCS} >= 0;
```

```
param cost

 [Pencils,*,*] (tr) Detroit  Denver :=
     Boston            10       40
    'New York'         20       40
     Seattle           60       30

 [Pens,*,*]    (tr) Detroit  Denver :=
     Boston            20       60
    'New York'         20       70
     Seattle           80       30    ;
```

Comparison

Model

gurobipy

```
m = Model('netflow')

flow = m.addVars(commodities, arcs, obj=cost, name="flow")

m.addConstrs(
  (flow.sum('*',i,j) <= capacity[i,j] for i,j in arcs), "cap")

m.addConstrs(
  (flow.sum(h,'*',j) + inflow[h,j] == flow.sum(h,j,'*')
     for h in commodities for j in nodes), "node")
```

alternatives

```
for i,j in arcs:
  m.addConstr(sum(flow[h,i,j] for h in commodities) <= capacity[i,j],
              "cap[%s,%s]" % (i,j))

m.addConstrs(
  (quicksum(flow[h,i,j] for i,j in arcs.select('*',j)) + inflow[h,j] ==
   quicksum(flow[h,j,k] for j,k in arcs.select(j,'*'))
     for h in commodities for j in nodes), "node")
```

(Note on Summations)

gurobipy quicksum

```
m.addConstrs(
  (quicksum(flow[h,i,j] for i,j in arcs.select('*',j)) + inflow[h,j] ==
   quicksum(flow[h,j,k] for j,k in arcs.select(j,'*'))
     for h in commodities for j in nodes), "node")
```

quicksum (data)

A version of the Python `sum` function that is much more efficient for building large Gurobi expressions (LinExpr or QuadExpr objects). The function takes a list of terms as its argument.

Note that while `quicksum` is much faster than `sum`, it isn't the fastest approach for building a large expression. Use addTerms or the LinExpr() constructor if you want the quickest possible expression construction.

Comparison

Model *(cont'd)*

AMPL

```
var Flow {COMMODITIES,ARCS} >= 0;

minimize TotalCost:
   sum {h in COMMODITIES, (i,j) in ARCS} cost[h,i,j] * Flow[h,i,j];

subject to Capacity {(i,j) in ARCS}:
   sum {h in COMMODITIES} Flow[h,i,j] <= capacity[i,j];

subject to Conservation {h in COMMODITIES, j in NODES}:
   sum {(i,j) in ARCS} Flow[h,i,j] + inflow[h,j] =
   sum {(j,i) in ARCS} Flow[h,j,i];
```

Comparison

Solution

gurobipy

```
m.optimize()

if m.status == GRB.Status.OPTIMAL:
    solution = m.getAttr('x', flow)
        for h in commodities:
            print('\nOptimal flows for %s:' % h)
            for i,j in arcs:
                if solution[h,i,j] > 0:
                    print('%s -> %s: %g' % (i, j, solution[h,i,j]))
```

```
Solved in 0 iterations and 0.00 seconds
Optimal objective  5.500000000e+03

Optimal flows for Pencils:
Detroit -> Boston: 50
Denver -> New York: 50
Denver -> Seattle: 10

Optimal flows for Pens: ...
```

Comparison

Solution *(cont'd)*

AMPL

```
ampl: solve;
Gurobi 8.1.0: optimal solution; objective 5500
2 simplex iterations

ampl: display Flow;

Flow [Pencils,*,*]
:        Boston 'New York' Seattle    :=
Denver      0       50        10
Detroit    50        0         0

 [Pens,*,*]
:        Boston 'New York' Seattle    :=
Denver     10        0        30
Detroit    30       30         0
;
```

Integration with Solvers

gurobipy

- Works closely with the Gurobi solver:
  callbacks during optimization, fast re-solves after problem changes
- Offers convenient extended expressions:
  min/max, and/or, if-then-else

AMPL

- Supports all popular solvers
- Extends to general nonlinear and logic expressions
  - Connects to nonlinear function libraries and user-defined functions
- Automatically computes nonlinear function derivatives

Comparison

Integration with Applications

gurobipy

- Everything can be developed in Python
  - Extensive data, visualization, deployment tools available
- Limited modeling features also in C++, C#, Java

AMPL

- Modeling language extended with loops, tests, assignments
- Application programming interfaces (APIs) for calling AMPL from C++, C#, Java, MATLAB, Python, R
  - Efficient methods for data interchange
- Add-ons for streamlined deployment
  - QuanDec by Cassotis
  - Opalytics Cloud Platform

Balanced Assignment Revisited

Given

P set of people

C set of categories of people

t_{ik} type of person i within category k, for all $i \in P, k \in C$

and

G number of groups

$g^{\min}$ lower limit on people in a group

$g^{\max}$ upper limit on people in a group

Define

$T_k = \bigcup_{i \in P} \{t_{ik}\}$, for all $k \in C$

set of all types of people in category k

Balanced Assignment Revisited *in AMPL*

Sets, parameters

```
set PEOPLE;   # individuals to be assigned

set CATEG;
param type {PEOPLE,CATEG} symbolic;

              # categories by which people are classified;
              # type of each person in each category

param numberGrps integer > 0;
param minInGrp integer > 0;
param maxInGrp integer >= minInGrp;

              # number of groups; bounds on size of groups


set TYPES {k in CATEG} = setof {i in PEOPLE} type[i,k];

              # all types found in each category
```

Balanced Assignment

Determine

$x_{ij} \in \{0,1\}$ $= 1$ if person i is assigned to group j
$= 0$ otherwise, for all $i \in P$, $j = 1, \ldots, G$

$y_{kl}^{\min}$ fewest people of category k, type l in any group,

$y_{kl}^{\max}$ most people of category k, type l in any group,
for each $k \in C$, $l \in T_k$

Where

$y_{kl}^{\min} \leq \sum_{i \in P: t_{ik} = l} x_{ij}$, for each $j = 1, \ldots, G$; $k \in C$, $l \in T_k$

$y_{kl}^{\max} \geq \sum_{i \in P: t_{ik} = l} x_{ij}$, for each $j = 1, \ldots, G$; $k \in C$, $l \in T_k$

Balanced Assignment *in AMPL*

Variables, defining constraints

```
var Assign {i in PEOPLE, j in 1..numberGrps} binary;

               # Assign[i,j] is 1 if and only if
               # person i is assigned to group j

var MinType {k in CATEG, TYPES[k]};
var MaxType {k in CATEG, TYPES[k]};

               # fewest and most people of each type, over all groups

subj to MinTypeDefn {j in 1..numberGrps, k in CATEG, l in TYPES[k]}:
   MinType[k,l] <= sum {i in PEOPLE: type[i,k] = l} Assign[i,j];

subj to MaxTypeDefn {j in 1..numberGrps, k in CATEG, l in TYPES[k]}:
   MaxType[k,l] >= sum {i in PEOPLE: type[i,k] = l} Assign[i,j];

               # values of MinTypeDefn and MaxTypeDefn variables
               # must be consistent with values of Assign variables
```

$$y_{kl}^{\max} \geq \sum_{i \in P: t_{ik}=l} x_{ij}, \text{ for each } j = 1, \ldots, G;\ k \in C, l \in T_k$$

Balanced Assignment

Minimize

$\sum_{k \in C} \sum_{l \in T_k} (y_{kl}^{\max} - y_{kl}^{\min})$

sum of inter-group variation over all types in all categories

Subject to

$\sum_{j=1}^{G} x_{ij} = 1$, for each $i \in P$

each person must be assigned to one group

$g^{\min} \leq \sum_{i \in P} x_{ij} \leq g^{\max}$, for each $j = 1, \ldots, G$

each group must be assigned an acceptable number of people

Balanced Assignment *in AMPL*

Objective, assignment constraints

```
minimize TotalVariation:
   sum {k in CATEG, l in TYPES[k]} (MaxType[k,l] - MinType[k,l]);

              # Total variation over all types

subj to AssignAll {i in PEOPLE}:
   sum {j in 1..numberGrps} Assign[i,j] = 1;

              # Each person must be assigned to one group

subj to GroupSize {j in 1..numberGrps}:
   minInGrp <= sum {i in PEOPLE} Assign[i,j] <= maxInGrp;

              # Each group must have an acceptable size
```

$g^{\min} \leq \sum_{i \in P} x_{ij} \leq g^{\max}$, for each $j = 1, \ldots, G$

Balanced Assignment

Define also

$$Q = \{i \in P : t_{i,\mathrm{m/f}} = \text{female}\}$$

Determine

$$z_j \in \{0,1\} = 1 \text{ if any women assigned to group } j$$
$$= 0 \text{ otherwise, for all } j = 1, \ldots, G$$

Subject to

$$2z_j \leq \sum_{i \in Q} x_{ij} \leq |Q|\, z_j, \text{ for each } j = 1, \ldots, G$$

each group must have either
no women $(z_j = 0)$ *or* ≥ 2 *women* $(z_j = 1)$

Balanced Assignment *in AMPL*

Supplemental constraints

```
set WOMEN = {i in PEOPLE: type[i,'m/f'] = 'F'};

var WomenInGroup {j in 1..numberGrps} binary;

subj to Min2WomenInGroupLO {j in 1..numberGrps}:
   2 * WomenInGroup[j] <= sum {i in WOMEN} Assign[i,j];

subj to Min2WomenInGroupUP {j in 1..numberGrps}:
   sum {i in WOMEN} Assign[i,j] <= card(WOMEN) * WomenInGroup[j];
```

$$2z_j \le \sum_{i\in Q} x_{ij} \le |Q|\, z_j, \text{ for each } j = 1,\ldots,G$$

Balanced Assignment

Modeling Language Data

210 people

```
set PEOPLE :=
   BIW   AJH   FWI   IGN   KWR   KKI   HMN   SML   RSR   TBR
   KRS   CAE   MPO   CAR   PSL   BCG   DJA   AJT   JPY   HWG
   TLR   MRL   JDS   JAE   TEN   MKA   NMA   PAS   DLD   SCG
   VAA   FTR   GCY   OGZ   SME   KKA   MMY   API   ASA   JLN
   JRT   SJO   WMS   RLN   WLB   SGA   MRE   SDN   HAN   JSG
   AMR   DHY   JMS   AGI   RHE   BLE   SMA   BAN   JAP   HER
   MES   DHE   SWS   ACI   RJY   TWD   MMA   JJR   MFR   LHS
   JAD   CWU   PMY   CAH   SJH   EGR   JMQ   GGH   MMH   JWR
   MJR   EAZ   WAD   LVN   DHR   ABE   LSR   MBT   AJU   SAS
   JRS   RFS   TAR   DLT   HJO   SCR   CMY   GDE   MSL   CGS
   HCN   JWS   RPR   RCR   RLS   DSF   MNA   MSR   PSY   MET
   DAN   RVY   PWS   CTS   KLN   RDN   ANV   LMN   FSM   KWN
   CWT   PMO   EJD   AJS   SBK   JWB   SNN   PST   PSZ   AWN
   DCN   RGR   CPR   NHI   HKA   VMA   DMN   KRA   CSN   HRR
   SWR   LLR   AVI   RHA   KWY   MLE   FJL   ESO   TJY   WHF
   TBG   FEE   MTH   RMN   WFS   CEH   SOL   ASO   MDI   RGE
   LVO   ADS   CGH   RHD   MBM   MRH   RGF   PSA   TTI   HMG
   ECA   CFS   MKN   SBM   RCG   JMA   EGL   UJT   ETN   GWZ
   MAI   DBN   HFE   PSO   APT   JMT   RJE   MRZ   MRK   XYF
   JCO   PSN   SCS   RDL   TMN   CGY   GMR   SER   RMS   JEN
   DWO   REN   DGR   DET   FJT   RJZ   MBY   RSN   REZ   BLW ;
```

Modeling Language Data

4 categories, 18 types, 12 groups, 16-19 people/group

```
set CATEG := dept loc 'm/f' title ;

param type:
     dept       loc     'm/f'   title   :=

BIW   NNE   Peoria         M   Assistant
KRS   WSW   Springfield    F   Assistant
TLR   NNW   Peoria         F   Adjunct
VAA   NNW   Peoria         M   Deputy
JRT   NNE   Springfield    M   Deputy
AMR   SSE   Peoria         M   Deputy
MES   NNE   Peoria         M   Consultant
JAD   NNE   Peoria         M   Adjunct
MJR   NNE   Springfield    M   Assistant
JRS   NNE   Springfield    M   Assistant
HCN   SSE   Peoria         M   Deputy
DAN   NNE   Springfield    M   Adjunct

.......

param numberGrps := 12 ;
param minInGrp := 16 ;
param maxInGrp := 19 ;
```

Balanced Assignment

Modeling Language Solution

Model + data = problem instance to be solved (CPLEX)

```
ampl: model BalAssign.mod;
ampl: data BalAssign.dat;

ampl: option solver cplex;
ampl: option show_stats 1;
ampl: solve;

2568 variables:
        2532 binary variables
        36 linear variables
678 constraints, all linear; 26328 nonzeros
        210 equality constraints
        456 inequality constraints
        12 range constraints
1 linear objective; 36 nonzeros.

CPLEX 12.9.0.0: optimal integer solution; objective 16
23690 MIP simplex iterations
159 branch-and-bound nodes
```

7.4 sec

Balanced Assignment

Modeling Language Solution

Model + data = problem instance to be solved (Gurobi)

```
ampl: model BalAssign.mod;
ampl: data BalAssign.dat;

ampl: option solver gurobi;
ampl: option show_stats 1;
ampl: solve;

2568 variables:
        2532 binary variables
        36 linear variables
678 constraints, all linear; 26328 nonzeros
        210 equality constraints
        456 inequality constraints
        12 range constraints
1 linear objective; 36 nonzeros.

Gurobi 8.1.0: optimal solution; objective 16
521639 simplex iterations
804 branch-and-cut nodes
```

109.1 sec

Extending a Modeling Language with Scripting

Example: Roll Cutting

- fill orders for rolls of various widths

Given

- raw rolls of a large (fixed) width
- demands for various (smaller) ordered widths
- a selection of cutting patterns that may be used

Determine

- the number of times to cut each pattern

So that

- demands are met (or slightly exceeded)
- *raw rolls cut* and *wasted material* are minimized

AMPL Model

Mathematical Formulation

Given

- w width of “raw” rolls
- W set of (smaller) ordered widths
- n number of cutting patterns considered

and

- a_{ij} occurrences of width i in pattern j, for each $i \in W$ and $j = 1, \ldots, n$
- b_i orders for width i, for each $i \in W$
- o limit on overruns

Mathematical Formulation *(cont'd)*

Determine

X_j number of rolls to cut using pattern j,
for each $j = 1, \ldots, n$

to minimize

$\sum_{j=1}^{n} X_j$

total number of rolls cut

subject to

$b_i \leq \sum_{j=1}^{n} a_{ij} X_j \leq b_i + o$, for all $i \in W$

number of rolls of width i cut
must be at least the number ordered,
and must be within the overrun limit

AMPL Formulation

Symbolic model

```
param rawWidth;
set WIDTHS;

param nPatterns integer > 0;
set PATTERNS = 1..nPatterns;

param rolls {WIDTHS,PATTERNS} >= 0, default 0;

param order {WIDTHS} >= 0;
param overrun;

var Cut {PATTERNS} integer >= 0;

minimize TotalCut: sum {p in PATTERNS} Cut[p];

subject to OrderLimits {w in WIDTHS}:
  order[w] <= sum {p in PATTERNS} rolls[w,p] * Cut[p] <= order[w] + overrun;
```

$$b_i \leq \sum_{j=1}^{n} a_{ij} X_j \leq b_i + o$$

AMPL Formulation *(cont'd)*

Explicit data (independent of model)

```
param rawWidth := 64.5 ;

param: WIDTHS: order :=
         6.77    10
         7.56    40
        17.46    33
        18.76    10 ;

param nPatterns := 9 ;

param rolls:  1  2  3  4  5  6  7  8  9 :=
       6.77   0  1  1  0  3  2  0  1  4
       7.56   1  0  2  1  1  4  6  5  2
      17.46   0  1  0  2  1  0  1  1  1
      18.76   3  2  2  1  1  1  0  0  0 ;

param overrun := 6 ;
```

AMPL Command Language

Model + data = problem instance to be solved

```
ampl: model cut.mod;
ampl: data cut.dat;

ampl: option solver cplex;

ampl: solve;

CPLEX 12.9.0.0: optimal integer solution; objective 20
3 MIP simplex iterations
0 branch-and-bound nodes

ampl: option omit_zero_rows 1;
ampl: option display_1col 0;

ampl: display Cut;

4 13    7 4    9 3
```

Command Language *(cont'd)*

Solver choice independent of model and data

```
ampl: model cut.mod;
ampl: data cut.dat;

ampl: option solver gurobi;

ampl: solve;

Gurobi 8.1.0: optimal solution; objective 20
3 simplex iterations
1 branch-and-cut nodes

ampl: option omit_zero_rows 1;
ampl: option display_1col 0;

ampl: display Cut;

4 13   7 4   9 3
```

AMPL Model

Command Language *(cont'd)*

Results available for browsing

```
ampl: display {p in PATTERNS} sum {w in WIDTHS} w * rolls[w,p];

1 63.84   3 59.41   5 64.09   7 62.82   9 59.66    # material used
2 61.75   4 61.24   6 62.54   8 62.0             # in each pattern


ampl: display sum {p in PATTERNS}
ampl?   Cut[p] * (rawWidth - sum {w in WIDTHS} w * rolls[w,p]);

62.32                                            # total waste
                                                 # in solution

ampl: display OrderLimits.lslack;

 6.77  0                                         # overruns
 7.56  0                                         # of each pattern
17.46  0
18.76  5
```

AMPL Script

Trade off two objectives

- Minimize rolls cut
  - Fewer overruns, possibly more waste
- Minimize waste
  - Less waste, possibly more overruns

```
minimize TotalCut:
   sum {p in PATTERNS} Cut[p];

minimize TotalWaste:
   sum {p in PATTERNS}
      Cut[p] * (rawWidth - sum {w in WIDTHS} w * rolls[w,p]);
```

Parametric Analysis of Tradeoff

Minimize rolls cut

- Set large overrun limit in data

Minimize waste

- Reduce overrun limit 1 roll at a time
- If there is a change in number of rolls cut
  - record total waste (increasing)
  - record total rolls cut (decreasing)
- Stop when no further progress possible
  - problem becomes infeasible *or*
  - total rolls cut falls to the minimum
- Report table of results

AMPL Script

Parametric Analysis *(cont'd)*

Script (setup and initial solve)

```
model cutTradeoff.mod;
data cutTradeoff.dat;

set OVER default {} ordered by reversed Integers;

param minCut;
param minCutWaste;
param minWaste {OVER};
param minWasteCut {OVER};

param prev_cut default Infinity;

option solver gurobi;
option solver_msg 0;

objective TotalCut;
solve >Nul;

let minCut := TotalCut;
let minCutWaste := TotalWaste;

objective TotalWaste;
```

AMPL Script

Parametric Analysis *(cont'd)*

Script (looping and reporting)

```
for {k in overrun .. 0 by -1} {
   let overrun := k;

   solve >Nul;

   if solve_result = 'infeasible' then break;

   if TotalCut < prev_cut then {
      let OVER := OVER union {k};
      let minWaste[k] := TotalWaste;
      let minWasteCut[k] := TotalCut;
      let prev_cut := TotalCut;
   }

   if TotalCut = minCut then break;
}

printf 'Min%3d rolls with waste%6.2f\n\n', minCut, minCutWaste;
printf ' Over  Waste  Cut\n’;
printf {k in OVER}: '%4d%8.2f%5d\n', k, minWaste[k], minWasteCut[k];
```

AMPL Script

Parametric Analysis *(cont'd)*

Script run

```
ampl: include cutWASTE.run

Min 20 rolls with waste 62.04

 Over  Waste  Number
  25   40.57    24
  19   43.01    23
  13   45.45    22
   7   47.89    21
   5   54.76    20

ampl:
```

Modeling Language APIs
(Application Programming Interfaces)

Example: Roll Cutting by Pattern Enumeration

- fill orders for rolls of various widths

Given

- Demands, raw width, orders, overrun limit at before
- pattern generation software
- result reporting software

Build optimization into an integrated application

- use AMPL for model-based optimization
- use a general-purpose programming language for overall control, pattern generation, and reporting

AMPL APIs

Principles

- ❖ APIs for "all" popular languages
  - ∗ C++, C#, Java, MATLAB, Python, R
- ❖ Common overall design
- ❖ Common implementation core in C++
- ❖ Customizations for each language and its data structures

Key to examples: Python and R

- ❖ AMPL entities
- ❖ AMPL API Python/R objects
- ❖ AMPL API Python/R methods
- ❖ Python/R functions etc.

AMPL Model File

Same pattern-cutting model

```
param nPatterns integer > 0;

set PATTERNS = 1..nPatterns;  # patterns
set WIDTHS;                   # finished widths

param order {WIDTHS} >= 0;    # rolls of width j ordered
param overrun;                # permitted overrun on any width

param rawWidth;                    # width of raw rolls to be cut
param rolls {WIDTHS,PATTERNS} >= 0, default 0;
                                   # rolls of width i in pattern j

var Cut {PATTERNS} integer >= 0;   # raw rolls to cut in each pattern

minimize TotalRawRolls: sum {p in PATTERNS} Cut[p];

subject to FinishedRollLimits {w in WIDTHS}:
   order[w] <= sum {p in PATTERNS} rolls[w,p] * Cut[p] <= order[w] + overrun;
```

Some Python Data

A float, an integer, and a dictionary

```
roll_width = 64.5

overrun = 6

Orders = {
     6.77: 10,
     7.56: 40,
    17.46: 33,
    18.76: 10
}
```

. . . can also work with lists and Pandas dataframes

Some R Data

A float, an integer, and a dataframe

```
roll_width <- 64.5

overrun <- 6

orders <- data.frame(

  width  = c( 6.77, 7.56, 17.46, 18.76 ),
  demand = c(   10,   40,    33,    10 )

)
```

Pattern Enumeration in Python

Load & generate data, set up AMPL model

```
def cuttingEnum(dataset):
  from amplpy import AMPL

  # Read orders, roll_width, overrun

  exec(open(dataset+'.py').read(), globals())

  # Enumerate patterns

  widths = list(sorted(orders.keys(), reverse=True))
  patmat = patternEnum(roll_width, widths)

  # Set up model

  ampl = AMPL()
  ampl.option['ampl_include'] = 'models'
  ampl.read('cut.mod')
```

Pattern Enumeration in R

Load & generate data, set up AMPL model

```
cuttingEnum <- function(dataset) {
  library(rAMPL)

  # Read orders, roll_width, overrun

  source(paste(dataset, ".R", sep=""))

  # Enumerate patterns

  patmat <- patternEnum(roll_width, orders$width)
  cat(sprintf("\n%d patterns enumerated\n\n", ncol(patmat)))

  # Set up model

  ampl <- new(AMPL)
  ampl$setOption("ampl_include", "models")
  ampl$read("cut.mod")
```

Pattern Enumeration in Python

Send data to AMPL

```
# Send scalar values

ampl.param['nPatterns'] = len(patmat)
ampl.param['overrun'] = overrun
ampl.param['rawWidth'] = roll_width

# Send order vector

ampl.set['WIDTHS'] = widths
ampl.param['order'] = orders

# Send pattern matrix

ampl.param['rolls'] = {
   (widths[i], 1+p): patmat[p][i]
   for i in range(len(widths))
   for p in range(len(patmat))
}
```

Pattern Enumeration in R

Send data to AMPL

```
# Send scalar values

ampl$getParameter("nPatterns")$set(ncol(patmat))
ampl$getParameter("overrun")$set(overrun)
ampl$getParameter("rawWidth")$set(roll_width)

# Send order vector

ampl$getSet("WIDTHS")$setValues(orders$width)
ampl$getParameter("order")$setValues(orders$demand)

# Send pattern matrix

df <- as.data.frame(as.table(patmat))
df[,1] <- orders$width[df[,1]]
df[,2] <- as.numeric(df[,2])

ampl$getParameter("rolls")$setValues(df)
```

Pattern Enumeration in Python

Solve and get results

```
# Solve

ampl.option['solver'] = 'gurobi'
ampl.solve()

# Retrieve solution

CuttingPlan = ampl.var['Cut'].getValues()
cutvec = list(CuttingPlan.getColumn('Cut.val'))
```

Pattern Enumeration in R

Solve and get results

```
# Solve

ampl$setOption("solver", "gurobi")
ampl$solve()

# Retrieve solution

CuttingPlan <- ampl$getVariable("Cut")$getValues()
solution <- CuttingPlan[CuttingPlan[,-1] != 0,]
```

Pattern Enumeration in Python

Display solution

```
# Prepare solution data

summary = {
    'Data': dataset,
    'Obj': int(ampl.obj['TotalRawRolls'].value()),
    'Waste': ampl.getValue(
                 'sum {p in PATTERNS} Cut[p] * \
                    (rawWidth - sum {w in WIDTHS} w*rolls[w,p])'
             )
}

solution = [
    (patmat[p], cutvec[p])
    for p in range(len(patmat))
    if cutvec[p] > 0
]


# Create plot of solution

cuttingPlot(roll_width, widths, summary, solution)
```

Pattern Enumeration in R

Display solution

```
  # Prepare solution data

  data <- dataset
  obj <- ampl$getObjective("TotalRawRolls")$value()

  waste <- ampl$getValue(
    "sum {p in PATTERNS} Cut[p] * (rawWidth - sum {w in WIDTHS} w*rolls[w,p])"
  )

  summary <- list(data=dataset, obj=obj, waste=waste)

  # Create plot of solution

  cuttingPlot(roll_width, orders$width, patmat, summary, solution)
}
```

Pattern Enumeration in Python

Enumeration routine

```
def patternEnum(roll_width, widths, prefix=[]):
  from math import floor

  max_rep = int(floor(roll_width/widths[0]))

  if len(widths) == 1:
      patmat = [prefix+[max_rep]]

  else:
     patmat = []
     for n in reversed(range(max_rep+1)):
        patmat += patternEnum(roll_width-n*widths[0], widths[1:], prefix+[n])

  return patmat
```

Pattern Enumeration in R

Enumeration routine

```
patternEnum <- function(roll_width, widths, prefix=c()) {

  cur_width <- widths[length(prefix)+1]
  max_rep <- floor(roll_width/cur_width)

  if (length(prefix)+1 == length(widths)) {
      return (c(prefix, max_rep))

  } else  {

      patterns <- matrix(nrow=length(widths), ncol=0)
      for (n in 0:max_rep) {
          patterns <- cbind(
              patterns,
              patternEnum(roll_width-n*cur_width, widths, c(prefix, n))
          )
      }
      return (patterns)
  }
}
```

Pattern Enumeration in Python

Plotting routine

```
def cuttingPlot(roll_width, widths, summ, solution):
    import numpy as np
    import matplotlib.pyplot as plt

    ind = np.arange(len(solution))
    acc = [0]*len(solution)

    colorlist = ['red','lightblue','orange','lightgreen',
                 'brown','fuchsia','silver','goldenrod']
```

Pattern Enumeration in R

Plotting routine

```
cuttingPlot <- function(roll_width, widths, patmat, summary, solution) {

  pal <- rainbow(length(widths))
  par(mar=c(1,1,1,1))
  par(mfrow=c(1,nrow(solution)))

  for(i in 1:nrow(solution)) {
    pattern <- patmat[, solution[i, 1]]
    data <- c()
    color <- c()}
```

Pattern Enumeration in Python

Plotting routine (cont'd)

```
for p, (patt, rep) in enumerate(solution):
   for i in range(len(widths)):
      for j in range(patt[i]):
         vec = [0]*len(solution)
         vec[p] = widths[i]
         plt.barh(ind, vec, 0.6, acc,
                  color=colorlist[i%len(colorlist)], edgecolor='black')
         acc[p] += widths[i]

plt.title(summ['Data'] + ": " +
   str(summ['Obj']) + " rolls" + ", " +
   str(round(100*summ['Waste']/(roll_width*summ['Obj']),2)) + "% waste"
   )

plt.xlim(0, roll_width)
plt.xticks(np.arange(0, roll_width, 10))
plt.yticks(ind, tuple("x {:}".format(rep) for patt, rep in solution))

plt.show()
```

AMPL API

Pattern Enumeration in R

Plotting routine (cont'd)

```
  for(j in 1:length(pattern)) {
      if(pattern[j] >= 1) {
        for(k in 1:pattern[j]) {
          data <- rbind(data, widths[j])
          color <- c(color, pal[j])
        }
      }
    }
    label <- sprintf("x %d", solution[i, -1])
    barplot(data, main=label, col=color,
            border="white", space=0.04, axes=FALSE, ylim=c(0, roll_width))
  }
  print(summary)
}
```

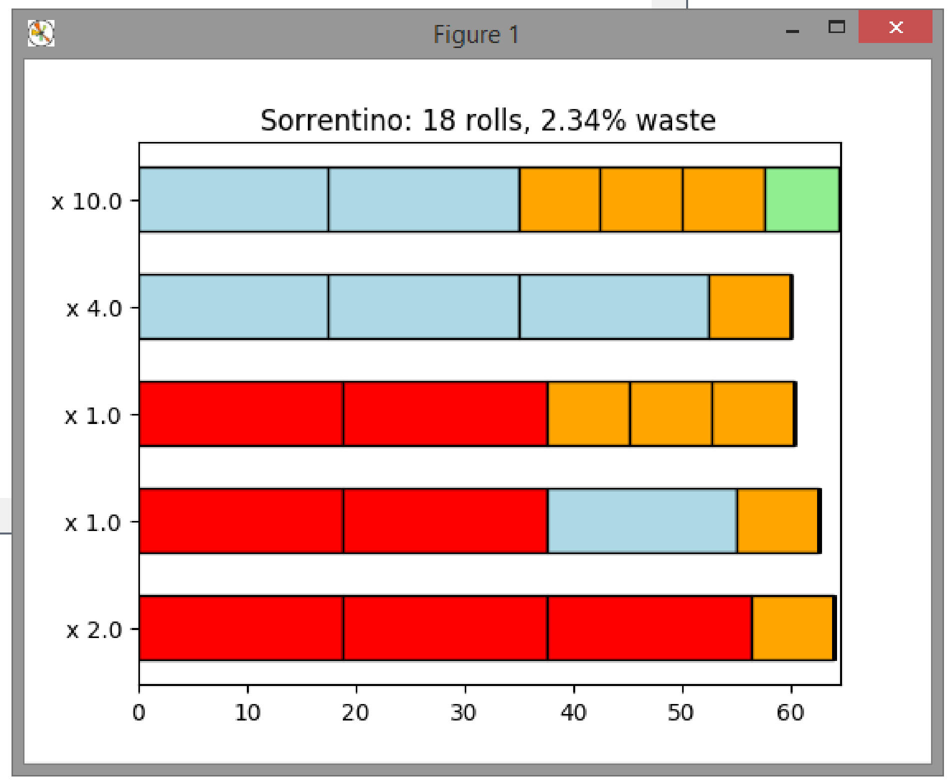
AMPL API

Pattern Enumeration in Python

Robert: running ipython

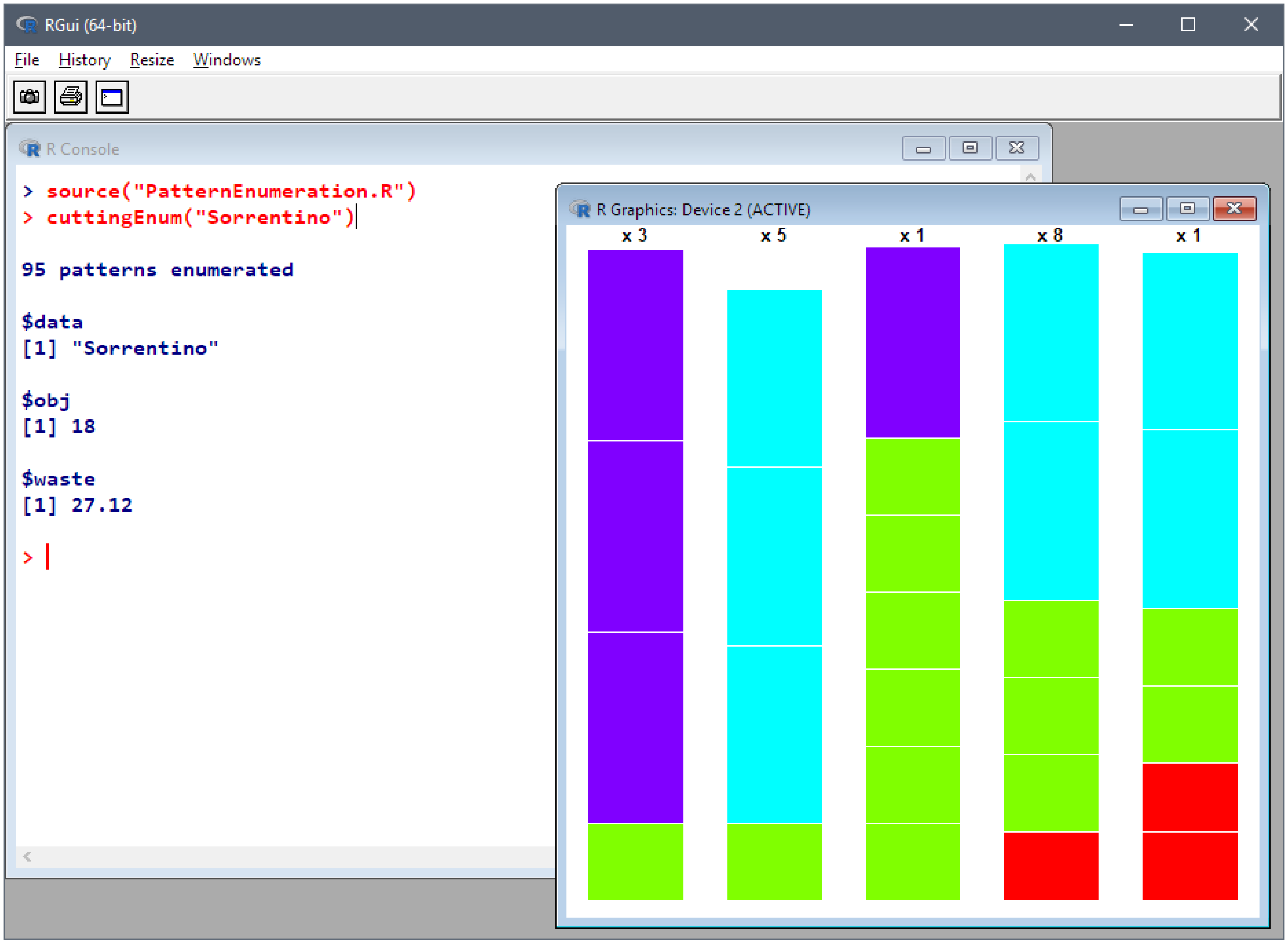
File Edit Help

```
sw: ipython
Python 3.6.4 (v3.6.4:d48eceb, Dec 19 2017, 06:54:40) [MSC v.1900 64 bit (AMD64)]
Type 'copyright', 'credits' or 'license' for more information
IPython 6.2.1 -- An enhanced Interactive Python. Type '?' for help.

In [1]: from pattern_enumeration import *

In [2]: cuttingEnum('Sorrentino')

43 patterns enumerated

Gurobi 8.1.0: optimal solution; objective 18
7 simplex iterations
1 branch-and-cut nodes
```



AMPL API

Pattern Enumeration in R



Modeling Language Integration with Python and Jupyter Notebooks

Example: Roll Cutting by Pattern Generation

- Sending Python data to an AMPL model
  - via AMPL API for Python
  - via Python references in the AMPL model
- Programming a custom stopping criterion in Python
  - via callbacks from the Gurobi solver
- Maintaining a view of the integrated application
  - via Jupyter notebooks

Example: Lot Sizing using Advanced Formulations

- Generating specialized constraints
  - via Python embedded in AMPL scripts

Sending Python Data to an AMPL model

Imported and generated data in Python

```
roll_width = 64.5

overrun = 6

orders = {
    6.77: 10,
    7.56: 40,
    17.46: 33,
    18.76: 10
}

patmat = patternEnum(roll_width, list(sorted(orders.keys(), reverse=True)))
```

Sending Data using the Python API

Symbolic sets and parameters in AMPL

cut.mod

```
param nPatterns integer > 0;

set PATTERNS = 1..nPatterns;
set WIDTHS;

param order {WIDTHS} >= 0;
param overrun;

param rawWidth;
param rolls {WIDTHS,PATTERNS} >= 0, default 0;
```

Sending Data using the Python API *(cont'd)*

Call `ampl` *methods to read model, send data*

```
ampl = AMPL()

.......

ampl.param['nPatterns'] = len(patmat)
ampl.param['overrun'] = overrun
ampl.param['rawWidth'] = roll_width

ampl.set['WIDTHS'] = widths
ampl.param['order'] = orders

ampl.param['rolls'] = {
    (widths[i], 1+p): patmat[p][i]
    for i in range(len(widths))
    for p in range(len(patmat))
}
```

Sending Data using PyMPL

Specify Python data correspondences in the model

cutpy.mod

```
ampl = AMPL(langext=PyMPL())

.......

$PARAM[nPatterns]{ len(patmat) };
set PATTERNS = 1..nPatterns;

$SET[WIDTHS]{ widths };

$PARAM[order{^WIDTHS}]{ orders };
$PARAM[overrun]{ overrun };

$PARAM[rawWidth]{ roll_width };
$PARAM[rolls {^WIDTHS,^PATTERNS}]{
    {
        (widths[i], 1+p): patmat[p][i]
        for i in range(len(widths))
        for p in range(len(patmat))
    }
};
```

Callbacks

Example: User-specified stopping rule

Data

- Times $t_1 < \mathrm{t}_2 < \mathrm{t}_3$ etc.
- Optimality gap tolerances $g_1 < g_2 < g_3$ etc.

Execution

- When elapsed time reaches t_i . . .
- Increase the gap tolerance to g_i

Callbacks

Stopping rule data in Python dictionary

stopping.py

```
stopdict = { 'time'   : (  15,    30,   60 ),
             'gaptol' : ( .0002, .002, .02 )
           }
```

Main routine for cutting by pattern generation

pattern_generation.py

```
def cuttingGen(cutdata, stopdata = ""):

  from amplpy import AMPL

  .......

  # begin pattern generation phase
  # finish when continuous relaxation of cutting problem has been solved
```

Python Integration

Callbacks

Set up callback and solve final integer program

```
# Instead of Master.solve(), export to a gurobipy object
grb_model = Master.exportGurobiModel()

# Assign AMPL stopping data to gurobipy objects
if len(stopdata) == 0:
  grb_model._stoprule = {'time': (1e+10,), 'gaptol': (1,)}
else:
  exec(open(stopdata+'.py').read(), globals())
  stopdict['time'] += (1e+10,)
  stopdict['gaptol'] += (1,)
  grb_model._stoprule = stopdict
grb_model._current = 0

# Solve and import results
grb_model.optimize(callback)
Master.importGurobiSolution(grb_model)
```

Callbacks

Callback function

```
def callback(m, where):
  """Gurobi callback function."""
  if where == gpy.GRB.Callback.MIP:
    runtime = m.cbGet(gpy.GRB.Callback.RUNTIME)
    if runtime >= m._stoprule['time'][m._current]:
      print("Reducing gap tolerance to %f at %d seconds" % \
        (m._stoprule['gaptol'][m._current], m._stoprule['time'][m._current]))
      m.Params.MIPGap = m._stoprule['gaptol'][m._current]
      m._current += 1
```

Executing Python inside AMPL

Fix AMPL variables according to Python variable

lotsize.mod

```
$PARAM[NT]{8};

var x {1..NT}, >= 0;   # production lot size
var y {1..NT}, binary; # production set-up
var s {0..NT}, >= 0;   # inventory level

var r {1..NT}, ${">= 0" if BACKLOG else ">= 0, <= 0"}$;

                                            # use these variables iff BACKLOG > 0
```

Embedded Python

Executing Python inside AMPL

Invoke Python generators for special lot-sizing constraints

lotsize.mod

```
$EXEC{

def mrange(a, b):
    return range(a, b+1)

s = ['s[{}]'.format(t) for t in mrange(0, NT)]
y = ['y[{}]'.format(t) for t in mrange(1, NT)]
d = [demand[t] for t in mrange(1, NT)]

if BACKLOG is False:
    WW_U_AMPL(s, y, d, NT, prefix='w')

else:
    r = ['r[{}]'.format(t) for t in mrange(1, NT)]
    WW_U_B_AMPL(s, r, y, d, NT, prefix='w')
};
```

```
ampl = AMPL(langext=PyMPL())
ampl.read('lotsize.mod')

ampl.solve()
```

Executing Python inside AMPL

Optional listing of generated constraints

```
var ws {wi in 0..8} = s[wi];
var wr {wi in 1..8} = r[wi];
var wy {wi in 1..8} = y[wi];

param wD {1..8, 1..8};

data;

param wD :=
[1,1]400 [1,2]800 [1,3]1600 [1,4]2400 [1,5]3600 [1,6]4800 [1,7]6000 [1,8]7200
[2,1]0   [2,2]400 [2,3]1200 [2,4]2000 [2,5]3200 [2,6]4400 [2,7]5600 [2,8]6800
[3,1]0   [3,2]0   [3,3]800  [3,4]1600 [3,5]2800 [3,6]4000 [3,7]5200 [3,8]6400
[4,1]0   [4,2]0   [4,3]0    [4,4]800  [4,5]2000 [4,6]3200 [4,7]4400 [4,8]5600
[5,1]0   [5,2]0   [5,3]0    [5,4]0    [5,5]1200 [5,6]2400 [5,7]3600 [5,8]4800
[6,1]0   [6,2]0   [6,3]0    [6,4]0    [6,5]0    [6,6]1200 [6,7]2400 [6,8]3600
[7,1]0   [7,2]0   [7,3]0    [7,4]0    [7,5]0    [7,6]0    [7,7]1200 [7,8]2400
[8,1]0   [8,2]0   [8,3]0    [8,4]0    [8,5]0    [8,6]0    [8,7]0    [8,8]1200
;

model;
```

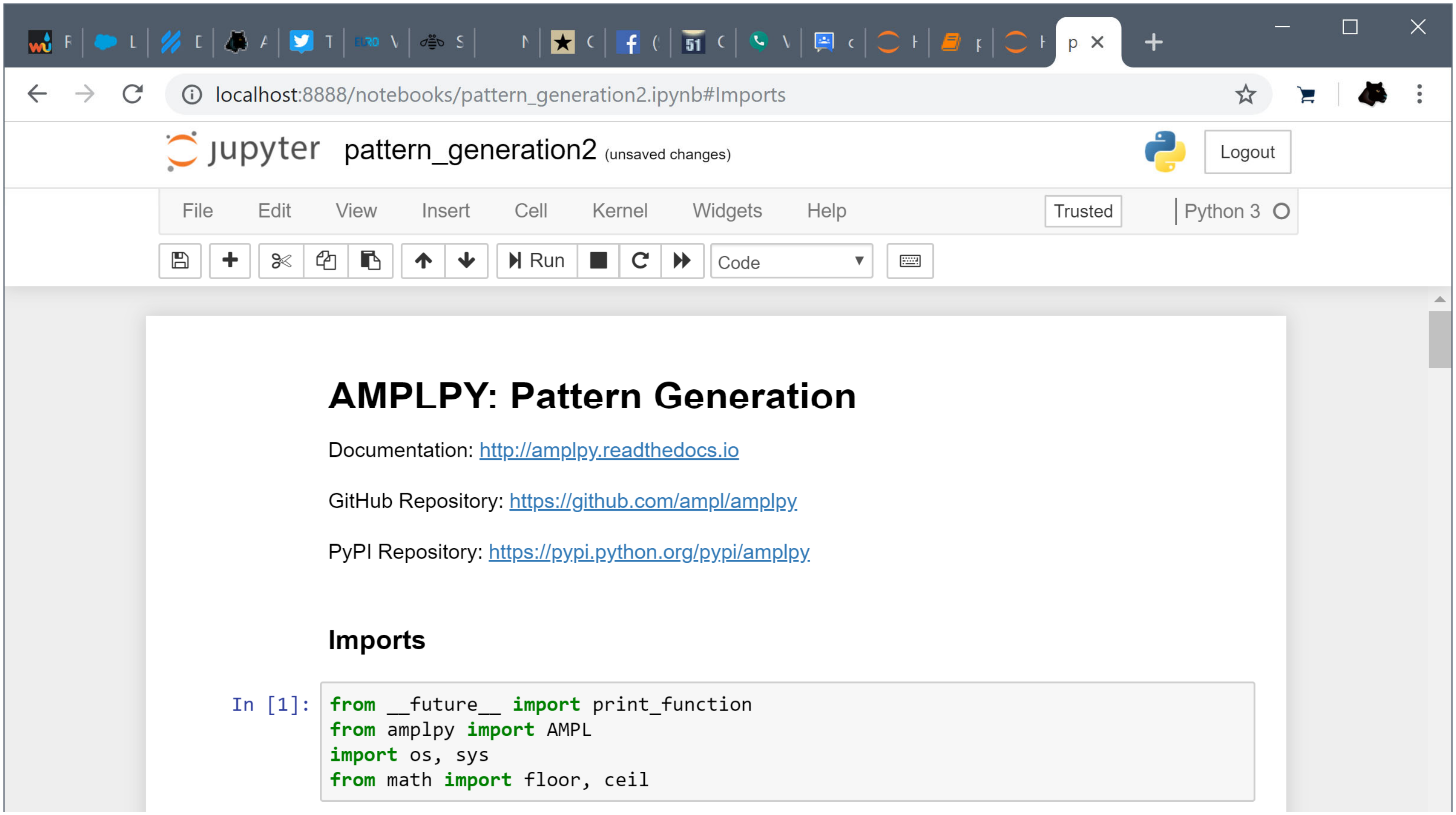
Executing Python inside AMPL

Optional listing of generated constraints (cont'd)

```
var wa {1..8};
var wb {1..8};

subject to wXY {wt in 1..8}: wa[wt] + wb[wt] + wy[wt] >= 1;

subject to wXA {wk in 1..8, wt in wk..min(8, wk+8-1): wD[wt,wt]>0}:

    ws[wk-1] >=
        sum {wi in wk..wt} wD[wi,wi] * wa[wi]
        - sum {wi in wk..wt-1} wD[wi+1,wt] * wy[wi];

subject to wXB {wk in 1..8, wt in max(1, wk-8+1)..wk: wD[wt,wt]>0}:

    wr[wk] >=
        sum {wi in wt..wk} wD[wi,wi] * wb[wi]
        - sum {wi in wt+1..wk} wD[wt,wi-1] * wy[wi];
```

AMPL in Jupyter Notebooks

Mix AMPL and Python cells



Building a Decision-Making Tool for Deployment

QuanDec

- Implemented in the Java API for AMPL
- Developed and supported by Cassotis Consulting

QuanDec

Architecture

Server side

- AMPL model and data
- Standard AMPL-solver installations

Client side

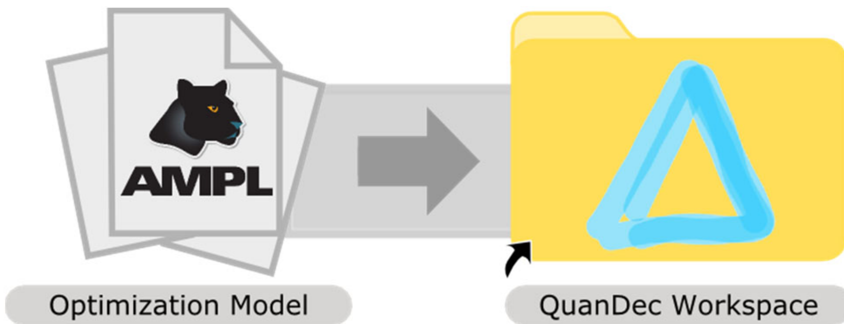
- Interactive tool for collaboration & decision-making
- Runs on any recent web browser
- Java-based implementation
  - AMPL API for Java
  - Eclipse Remote Application Platform

Getting Started

step 1: install QuanDec on a server

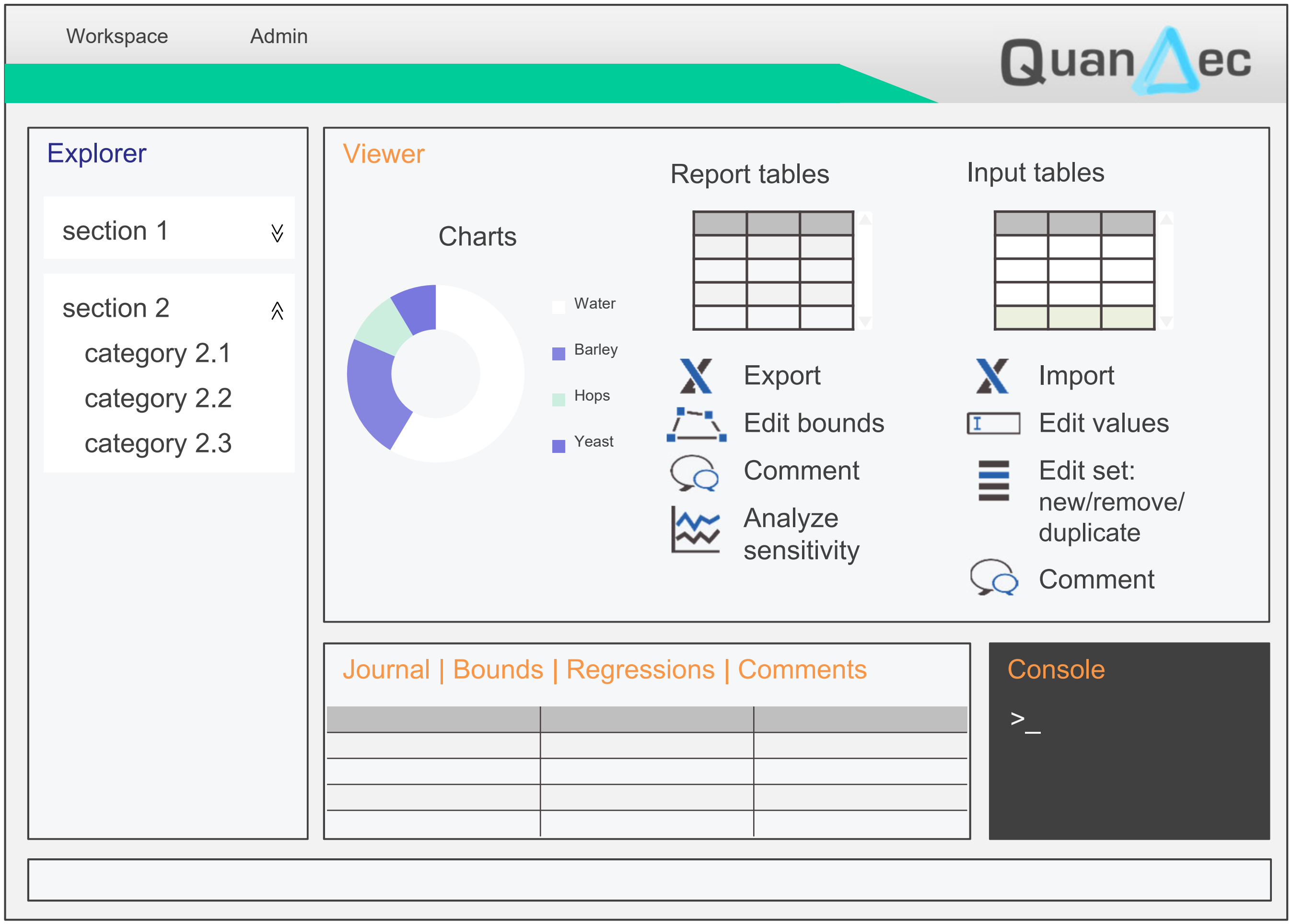
step 2: copy & paste your model files (.mod and .dat) into QuanDec's workspace

step 3: create AMPL tables and link them to QuanDec explorer



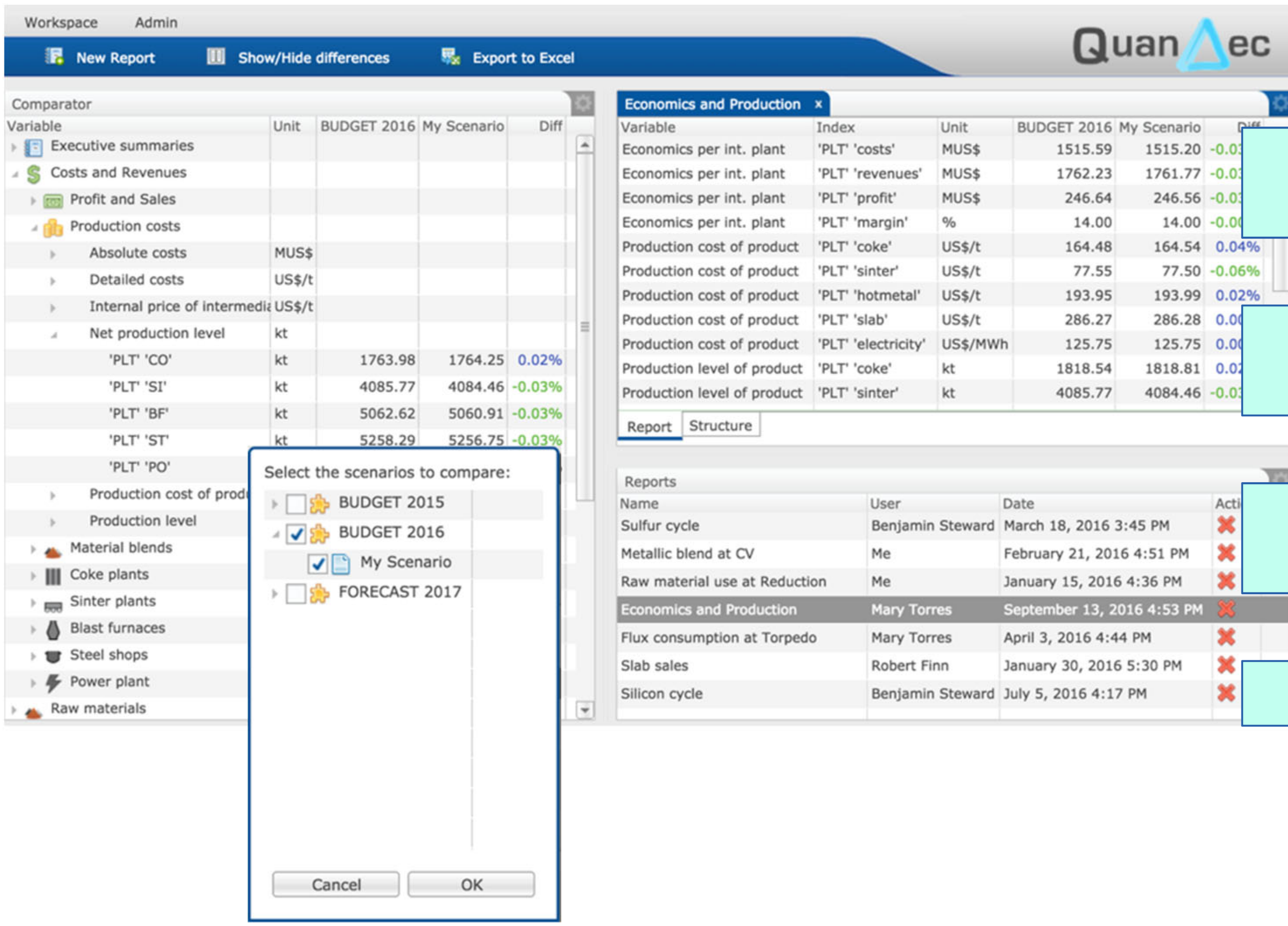
QuanDec

Workbench



QuanDec

Scenarios



Scenario comparison

All variables can be compared

Display of relative difference

Custom reports