Digital Technologies and Value Creation

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Overview – subject to change

Overarching theme	Week	
Introduction	1	Introduction to analytics applications and coding basics
Gathering data	2	Scraping web data
Gathering data / descriptive analytics	3	Data pre-processing and descriptive analytics
Gathering data / descriptive analytics	4	Descriptives in marketing analytics, and using social media APIs
Descriptive analytics	5	Descriptives in people analytics
NO LECTURE	6	NO LECTURE
Predictive analytics	7	Retaining employees and customers with classification
Predictive analytics	8	Wrapping up classification and a deep-dive into dimensionality reduction
Predictive analytics	9	Segmenting customers and positioning products
Prescriptive analytics	10	Optimizing products and organizations
Prescriptive analytics	11	A/B-testing in practice

Learning objectives of today

Goals:

- Recap the ideas behind optimization and linear programming
- Understand integer programming and how it is different from linear programming
- Learn how to formulate integer programs and solve them in Excel Solver

How will we do this?

- Exercises in Linear and Integer Programming

Recap: optimization

What is optimization?

- Optimization = making the most out of any situation
- You routinely solve optimization problems in your everyday life:

What to eat at lunch?

- Maximize healthiness
- Or maximize pleasure?

- Don’t want to eat same as yesterday
- Vegetarian
- Not eat something I could spill on myself

How to organize my week?

- Maximize long periods with nothing to do

- Certain amount of homework to be done
- No work on Saturday evenings/Sundays
- Need to eat (and sleep?)

Building blocks of optimization

All these examples have three commonalities: these are the building blocks of optimization.

Decision variables	What you have control over to change, the alternatives you choose among many
Objective	Quantity that you are trying to maximize or minimize
Constraints	Restrictions on what your decision variables can be

Always, always start with **decision variables. Always**.

Optimization in companies

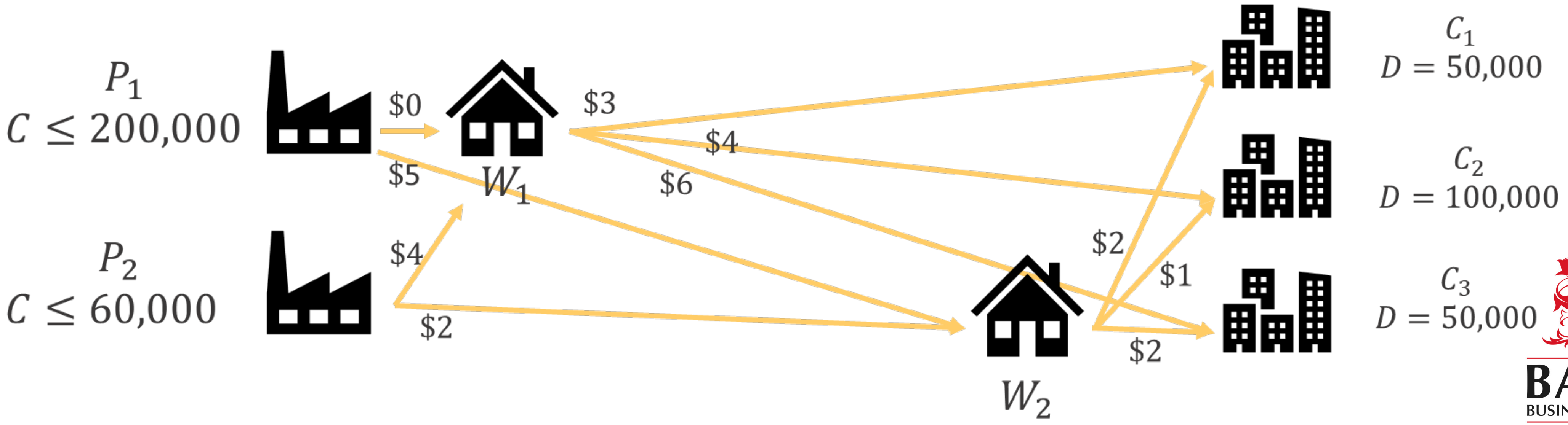
- **Finance**: how to invest money into stocks to maximize profit
- **Revenue management and pricing**: how to price tickets or goods so as to maximize occupancy
- **Resource allocation:** how to allocate goods (e.g., rooms, staff, etc.) or other resources (e.g., budgets) while respecting everyone's constraints
  - Marketing: how much budget to allocate to each campaign?
  - Organizational design: how much budget to allocate to different development programs?
- **Routing:** shortest path to take (e.g., Google Maps)
- **Facility location:** where to construct a new facility? Which facility to close?
- And many more…

Recap: linear programming

A distribution example

We direct the logistics for a firm that produces and manages

- A single product
- Two plants: P1 with capacity 200,000 units and P2 with capacity 60,000. The manufacturing costs are identical.
- Two warehouses with equal holding costs: W1 close to production, W2 close to the customers
- Three customer regions C1, C2, C3 with demands 50,000, 100,000, and 50,000 units



Modeling the problem

Decision variables: how much we ship from one place to another.

- Plants to warehouses: $x_{P_1\to W_1}, x_{P1\to W_2}, x_{P_2\to W_1}, x_{P_2\to W_2}$
- Warehouses to customers: $x_{W_1\to C_1}, x_{W_1\to C_2}, x_{W_1\to C_3}, x_{W_2\to C_1}, x_{W_2\to C_2}, x_{W_2\to C_3}$

Constraints: in = out, demand satisfied, capacity.

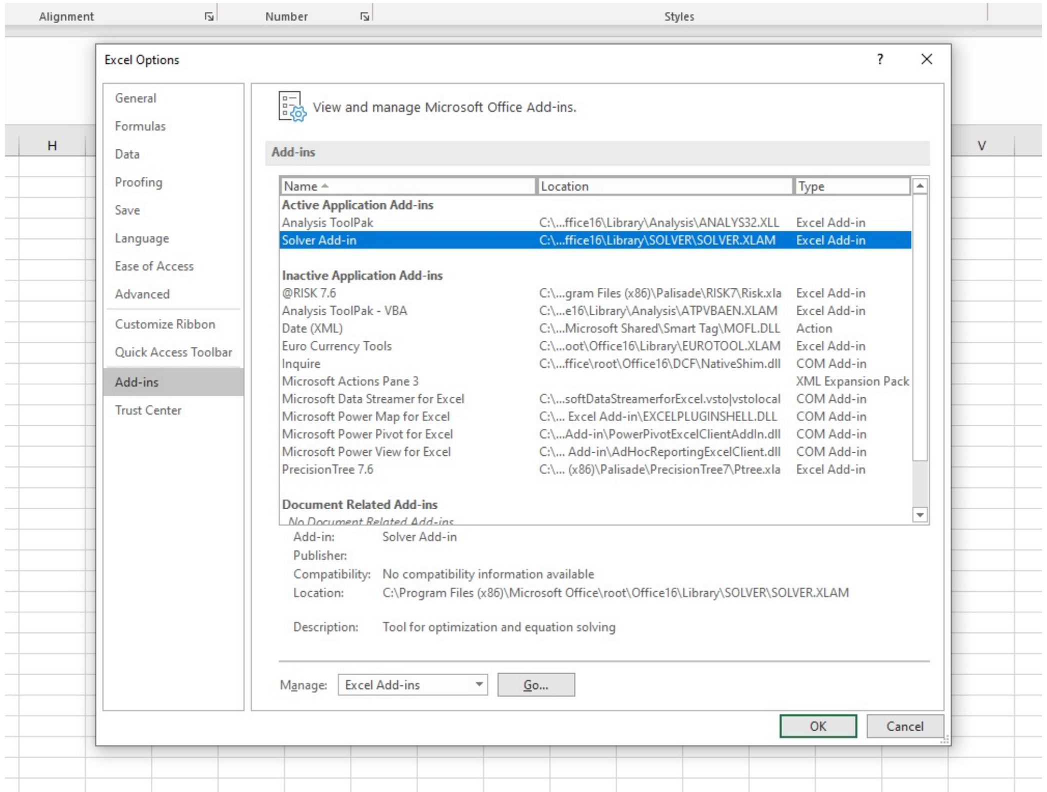
- In=out at W_1: $x_{P_1\to W_1} + x_{P_2\to W_1} = x_{W_1\to C_1} + x_{W_1\to C_2} + x_{W_1\to C_3}$
- In=out at W_2: $x_{P_1\to W_2} + x_{P_2\to W_2} = x_{W_2\to C_1} + x_{W_2\to C_2} + x_{W_2\to C_3}$
- Capacity: $x_{P_1\to W_1} + x_{P_1\to W_2} \leq 200{,}000$ and $x_{P_2\to W_1} + x_{P_2\to W_2} \leq 60{,}000$
- Demand satisfied: $x_{W_1\to C_1} + x_{W_2\to C_1} \geq 50{,}000$ and $x_{W_1\to C_2} + x_{W_2\to C_2} \geq 100{,}000$ and $x_{W_1\to C_3} + x_{W_2\to C_3} \geq 50{,}000$
- Quantities are nonnegative: $x_{P_1\to W_1} \geq 0, x_{P1\to W_2} \geq 0, \ldots$

Objective: minimize cost

- $0x_{P_1\to W_1} + 5x_{P1\to W_2} + 4x_{P_2\to W_1} + 2x_{P2\to W_2} + 3x_{W_1\to C_1} + 4x_{W_1\to C_2} + 6x_{W_1\to C_3} + 2x_{W_2\to C_1} + x_{W_2\to C_2} + 2x_{W_2\to C_3}$

Solvers

- Any solver takes an optimization problem as input in a “standard” form and outputs a solution.
- We will use the Excel solver (visual, easy to use)
- But of course, there are many other solvers (also in Python!)



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Linear programs more generally

A linear program only has **constraints that are linear combinations of the decision variables**, i.e.,

$$a_0 + a_1x_1 + \cdots + a_nx_n \leq 0$$
$$a_0 + a_1x_1 + \cdots + a_nx_n \geq 0$$
$$a_0 + a_1x_1 + \cdots + a_nx_n = 0$$

where $x_1, \ldots, x_n$ are the decision variables.

A linear program only has an **objective that is linear**, i.e.:

$$c_0 + c_1x_1 + \cdots + c_nx_n$$

We know how to solve linear programs **really fast** and we can guarantee that the solution we obtain is **correct.**

Modeling and solving a new situation

A coffee packer blends Brazilian coffee and Colombian coffee to prepare two products, super and deluxe brands.

Each kilogram of super coffee contains 0.5 kg of Brazilian coffee and 0.5 kg of Colombian coffee, whereas each kilogram of deluxe coffee contains 0.25 kg of Brazilian coffee and 0.75 kg of Colombian coffee.

The packer has 120kg of Brazilian coffee and 160kg of Colombian coffee on hand.

If the profit for each kilogram of super coffee is 20 cents and the profit for each kilogram of deluxe coffee is 15 cents, how many kilograms of each type of coffee should be blended to maximize profits?

1. What are the decision variables?
2. What are the constraints?
3. What is the objective?
4. Solve the problem using the Excel Solver!

Step 1: decision variables

A coffee packer blends Brazilian coffee and Colombian coffee to prepare two products, super and deluxe brands.

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If the profit for each kilogram of super coffee is 20 cents and the profit for each kilogram of Deluxe coffee is 15 cents, how many kilograms of each type of coffee should be blended to maximize profits?

Decision variables

x_s: kilograms of super brand to sell

x_d: kilograms of deluxe brand to sell

Step 2: constraints

A coffee packer blends Brazilian coffee and Colombian coffee to prepare two products, super and deluxe brands.

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If the profit for each kilogram of super coffee is 20 cents and the profit for each kilogram of Deluxe coffee is 15 cents, how many kilograms of each type of coffee should be blended to maximize profits?

Constraints

120kg of Brazilian coffee to use: $0.5\ x_s + 0.25\ x_d \leq 120$

160kg of Colombian coffee to use: $0.5\ x_s + 0.75\ x_d \leq 160$

Quantities can't be negative: $x_s \geq 0, x_d \geq 0$

Step 3: objective

A coffee packer blends Brazilian coffee and Colombian coffee to prepare two products, super and deluxe brands.

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The packer has 120kg of Brazilian coffee and 160kg of Colombian coffee on hand.

If the profit for each kilogram of super coffee is 20 cents and the profit for each kilogram of Deluxe coffee is 15 cents, how many kilograms of each type of coffee should be blended to maximize profits?

Objective

Maximize profit: $0.2\,x_s + 0.15\,x_d$

Step 4: solve the problem with the Excel solver

From linear to integer programming

Limits of Linear Programming

All previous examples assume that the quantities we use (e.g., products to ship, coffee to sell) can be **any number.**

If we had scheduled people instead of units of product, we could not have done this: what is 2.6367 persons?

Integer programming is **linear programming** with **additional constraints** added on:

- Can require that our variables be **binary (0/1)**
- Can require that our variables be **integers (0,1,2,…)**

So objective = linear, constraints = linear + binary/integer constraints

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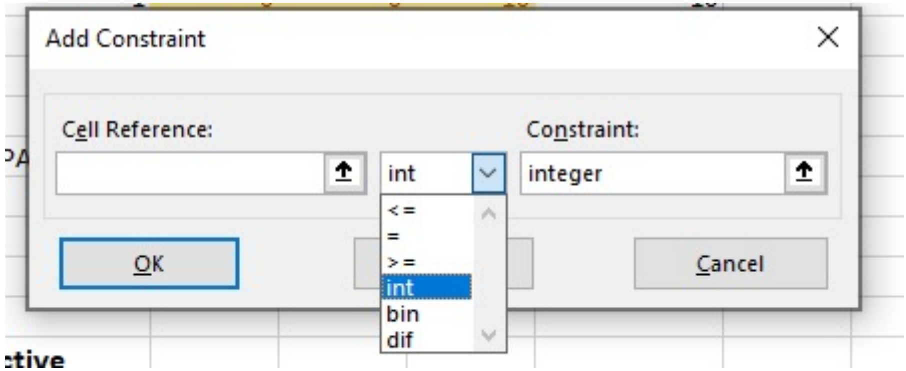
How to add these constraints in the Excel Solver?



If that's all, what's the big deal?

- Integer programs are **more complex** than linear programs

- **No free lunch**:
  - Linear programs can be solved to optimality **always in a reasonable time**
  - **Integer programs** can be solved to optimality but sometimes **in exponential (=very long) time.** With our time constraints, this can mean the solution we sometimes get is **not optimal.**

- Why can't I just take my integer program, make it linear by removing the additional constraints and then round the solution I get to integer?

You can but the solution you'll get is not necessarily optimal.

Activity: IP in practice

Open *Week 10_Lecture_Activity.pdf*

Work on Situations 1 and 2

Situation 1:

Decision variables: how many advent calendars of each brand to put out in our display? Represent this using **integer variables!**

Constraints: surface, min number, weight

Objective: maximize margin made

Decision Vars			
	Brand 1	Brand 2	Brand 3
How much to expose	12.00	10.00	24.00

	Objective
Maximize	65.6

Situation 2:

Decision variables: which project should we invest it?
Represent this using **binary variables:**

$x_1 = 1$ if we invest in project 1, 0 otherwise

Same for $x_2, \ldots, x_6$

Constraints:
Initial investment less than 4M:

$$1.3x_1 + 0.8x_2 + 0.6x_3 + 1.8x_4 + 1.2x_5 + 2.4x_6 \leq 4$$

If the investment is taken on then the cost appears. Otherwise, it is multiplied by 0 and disappears.

Situation 2:

Constraints:

Average failure risk less than 5%

Number of projects taken on: $x_1 + \cdots + x_6$

Total Failure risk: $6\%\, x_1 + 4\%\, x_2 + 6\%\, x_3 + 5\%\, x_4 + 5\%\, x_5 + 4\%\, x_6$

We should write:

$$\frac{6\%\, x_1 + 4\%\, x_2 + 6\%\, x_3 + 5\%\, x_4 + 5\%\, x_5 + 4\%\, x_6}{x_1 + x_2 + x_3 + x_4 + x_5 + x_6} \leq 5\%$$

Issue: it is non-linear!
How to get around this?

$$6\%\, x_1 + 4\%\, x_2 + 6\%\, x_3 + 5\%\, x_4 + 5\%\, x_5 + 4\%\, x_6 \leq 5\%(x_1 + \cdots + x_6)$$
$$1\%\, x_1 - 1\%\, x_2 + 1\%\, x_3 + 0\%\, x_4 + 0\%\, x_5 - 1\%\, x_6 \leq 0$$

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Situation 2:

Objective: maximize total expected profit

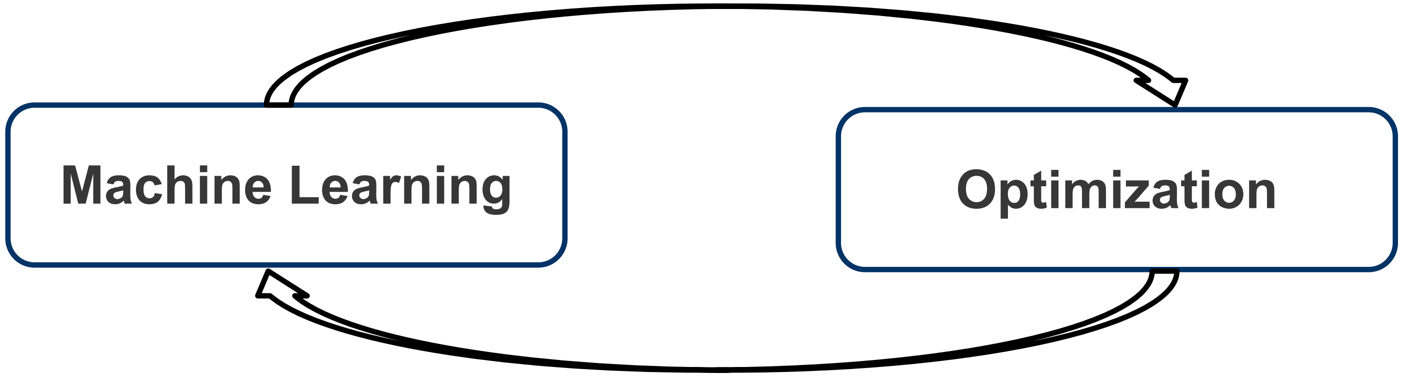
Decision variables						
	P1	P2	P3	P4	P5	P6
Invest or not?	0.00	1.00	1.00	0.00	0.00	1.00

	Objective
Maximize	50

Machine learning and optimization

The link between Machine Learning and Optimization

Predictions from a machine learning algorithm can be used as input to an optimization problem



(Nearly) all machine algorithms solve an optimization problem in the background

Integration planning at SFB

- An (award-winning) case in 3 parts
- Overarching question: how to reduce the headcount after a merger?

- Société Française de Biotechnologie (SFB) was acquired by Big American Pharmaceuticals (BAP), and there should be synergies, so we need less employees
- In France (and Europe more generally), we cannot just fire employees after a merger
- What we can do: offer attractive severance packages to give dissatisfied employees a chance to leave (In France: RCC). There are conditions
    - RCCs have to be offered to larger groups, not individuals or groups of just a few people
    - Groups have to be defined objectively and cannot be based on protected characteristics
    - We cannot choose our groups so that employees are implicitly discriminated

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A data-driven approach

- First, we need to figure out how likely employees are to take the RCC. Luckily, we have “training data” from a previous company merger where everyone was offered an RCC

  → predict probabilities of employees in the current case accepting an RCC

- Next, we want to use our predictions to decide who should be offered an RCC
  - Clearly, this is an optimization problem
  - However, remember that we cannot target individuals → What are the decision variables?
  - …

See you next week!