PGE 338 Data Analytics and Geostatistics

Lecture 16c: Decision Making

Lecture outline . . .

- Decision Making
- Loss Functions
- Decision Making Example
- Decision Making Hands-on

Introduction

General Concepts

Univariate

Bivariate

Spatial

- Calculation
- Variogram Modeling
- Kriging
- Simulation

Time Series

Machine Learning

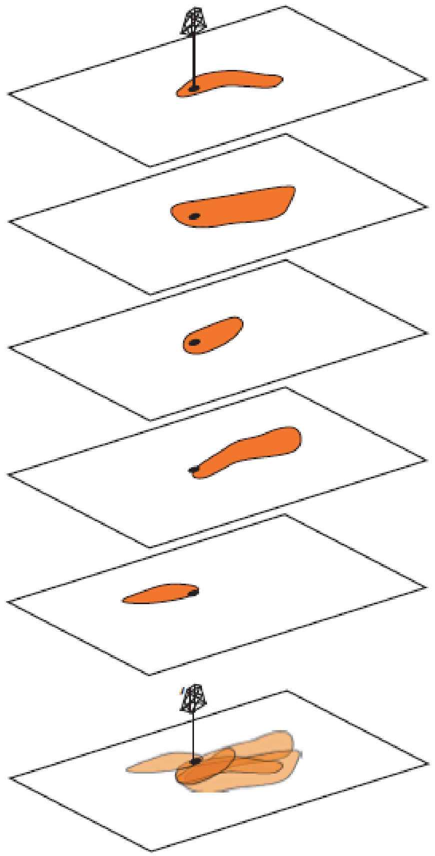
Uncertainty Analysis

Michael Pyrcz, The University of Texas at Austin

Motivation

We have built uncertainty models,

now we need to make decisions in the presence of uncertainty.



Multiple reservoir realizations to represent uncertainty, but we must make a single choice, where to put the well.

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- Decision Making

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Recall: Uncertainty Models

How Did We Calculate Uncertainty Models? Some examples:

1. **Bayesian Updating**
   - prior plus likelihood to calculate the posterior
   - e.g., probability that a coin is fair, uncertainty in reservoir OIP

2. **Bootstrap + Monte Carlo Simulation and Transfer Function**
   - uncertainty mean porosity by bootstrap, then MCS for uncertainty in OIP

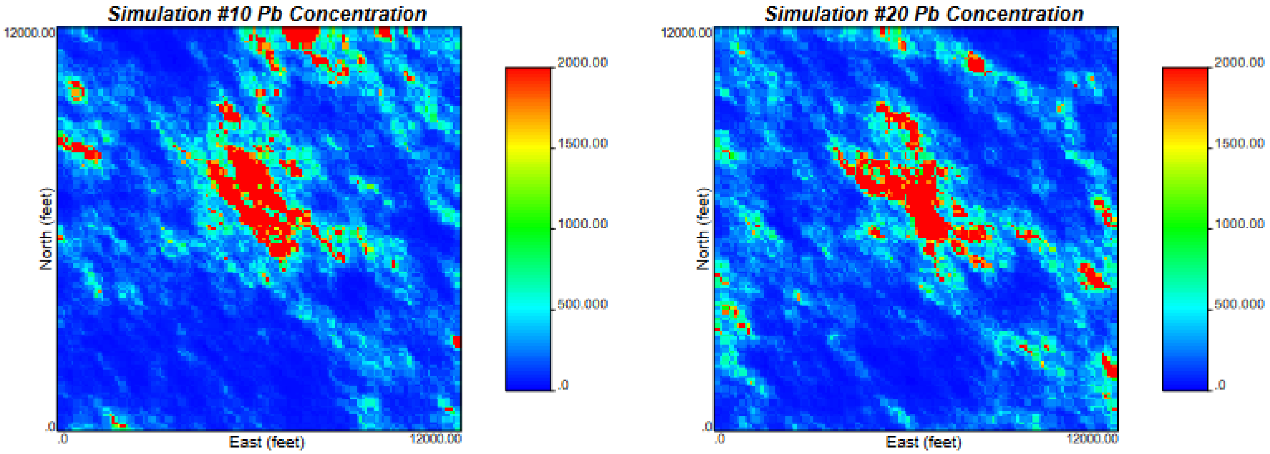
3. **Kriging**
   - kriging estimate and variance with Gaussian assumption for uncertainty at a location
   - indicator kriging of uncertainty at a location

4. **Simulation and Transfer Function**
   - reservoir realizations applied to flow simulation to calculate pre-drill production uncertainty at a new well

Subsurface Decision Making

We have calculated a reasonable uncertainty model, e.g.:

- Connected volume of water or hydrocarbon to a location
- Mineral or hydrocarbon resource in place
- Recover factor mineral or hydrocarbon extraction



Two realizations of soil lead concentration from Dallas, Texas (Pyrcz, 2000). Units are PPM.

We must make a decision with that uncertainty model

- Number and locations of wells
- Time and volume injected for water of chemical flood, pump and treat remediation
- Dig limits and mine plan

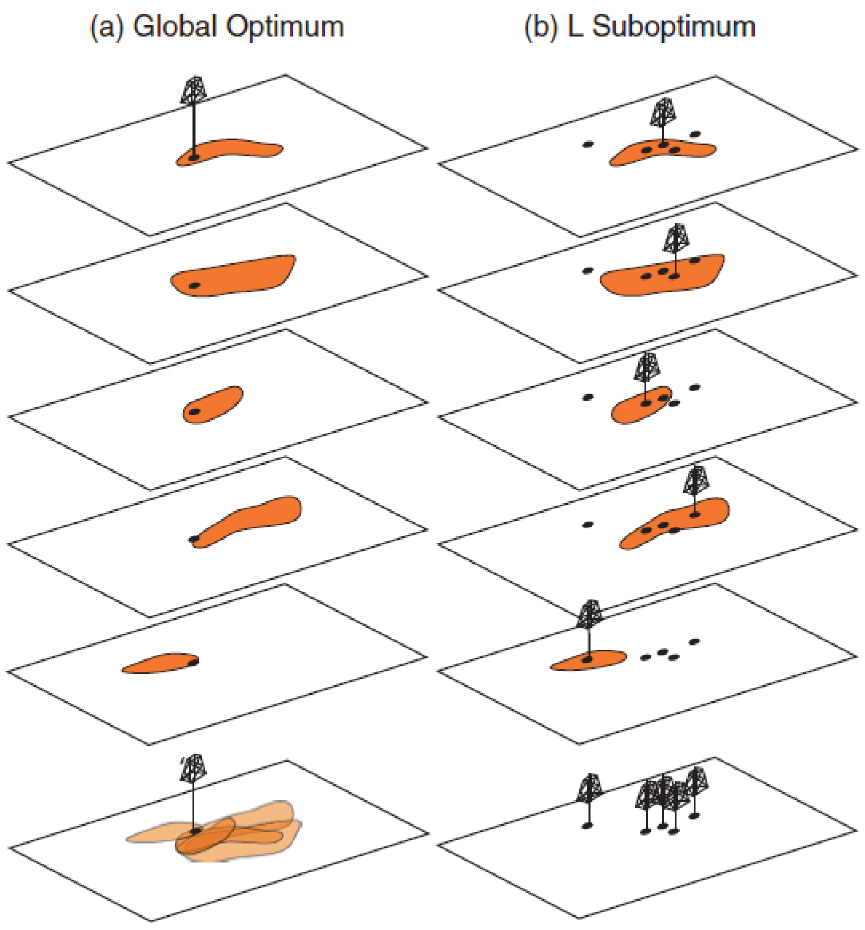
Types of Decisions

Well site selection methods:

- **Integer programing** problem, output must be an integer, not a fraction
- **Optimization** combined with **simulation** one potential well at a time
- **Experimental design** and response surface methodology

Optimize the profitability of reservoir production

- **High dimensional**: complicated by large number of parameters and timing
- **Interactions**: locations of injector and producers,
- **Multivariate**: injection, well completions



Global optimum vs. L suboptimum (Pyrcz and Deutsch, 2014).

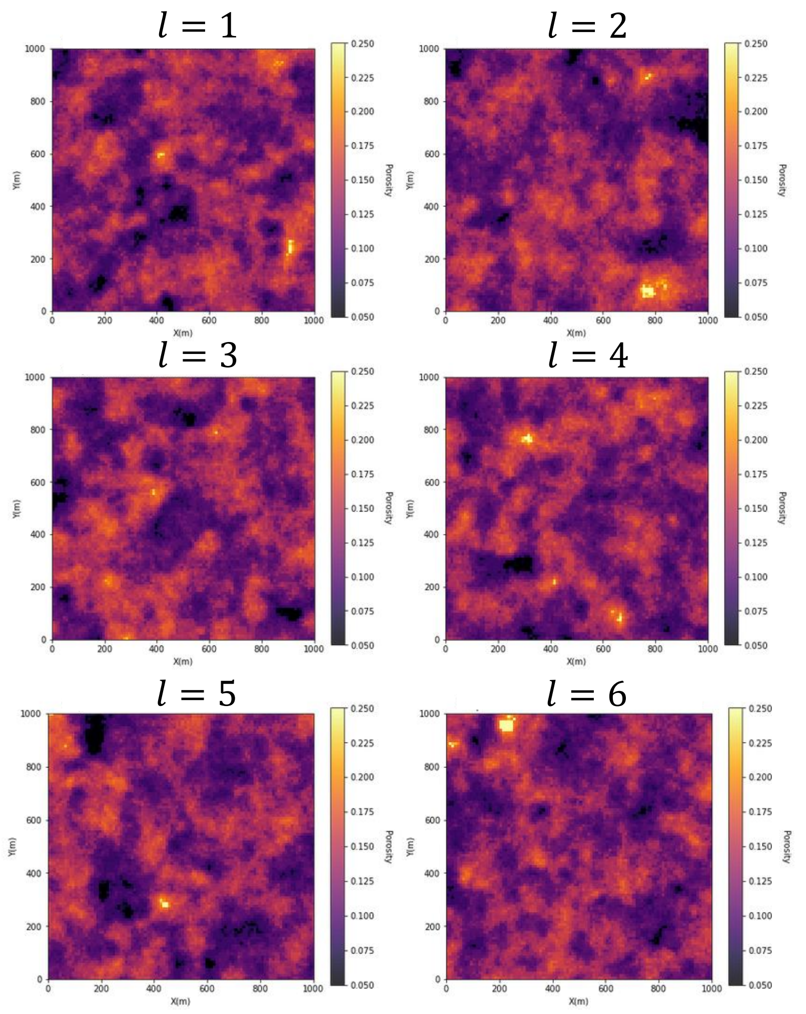
Decision Making by Maximizing Expected Value

Expected Profit Workflow:

1. Calculate the uncertainty model, $\boldsymbol{l = 1, \ldots, L}$ **subsurface realizations**

The Uncertainty Model

- **Scenarios** change the model inputs, and assumptions to capture uncertainty in the modeling decisions.
- **Realizations** change the random number seed to capture spatial uncertainty
- **Multivariate**, includes all features needed to simulate extraction.
- The **uncertainty model** is represented by multiple models of the subsurface.



$l = 1, \ldots, 6$ subsurface models, realizations and scenarios of the subsurface.

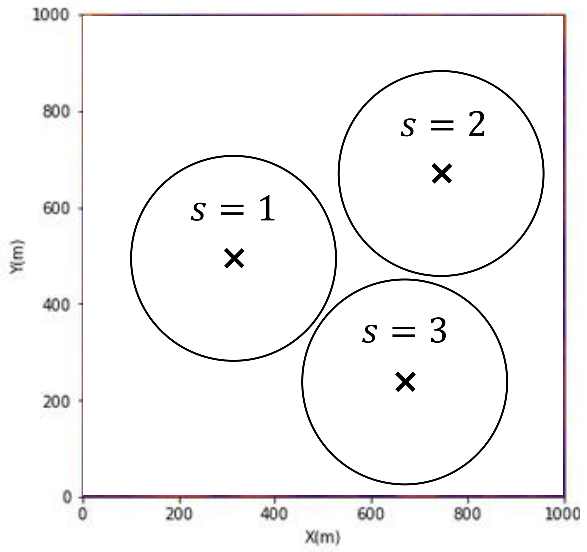
Decision Making by Maximizing Expected Value

Expected Profit Workflow:

1. Calculate the uncertainty model, $\boldsymbol{L}$ **subsurface realizations**
2. Establish $\boldsymbol{s = 1, \ldots, S}$ **development scenarios**

The Development Scenarios

- **Discrete alternatives** for developing the spatial, subsurface resource
- Includes all **details needed to simulate extraction**, e.g., well locations, completion types, dig limits, mining block sequence
- **For example,** 3 potential well locations with drainage radius.



$s = 1, \ldots, 3$ development scenarios.

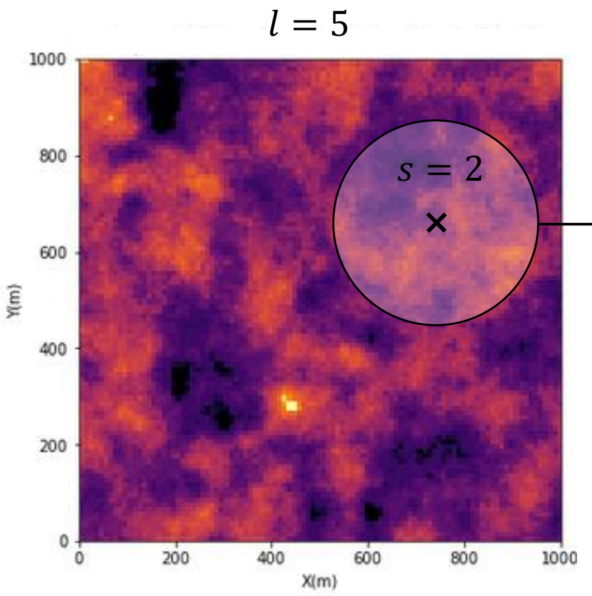
Decision Making by Maximizing Expected Value

Expected Profit Workflow:

1. Calculate the uncertainty model, $\boldsymbol{L}$ **subsurface realizations**
2. Establish $\boldsymbol{S}$ **development scenarios**
3. Establish $\boldsymbol{P}$ **profit metric**

The Profit Metric

- **Transfer function** to map from spatial features to value, $\boldsymbol{P}(\boldsymbol{l},\boldsymbol{s})$
- **Input** is a subsurface realization, $\boldsymbol{l}$, and development scenario, $\boldsymbol{s}$.
- **In the thing are we trying to maximize**? E.g., net present value, contaminant removed from soil, resource recovered.



$l = 5$, realization, $s = 2$ development scenario.

$\boldsymbol{P}(\boldsymbol{l} = \mathbf{5}, \boldsymbol{s} = \mathbf{2})$ = **13 MMbbls**

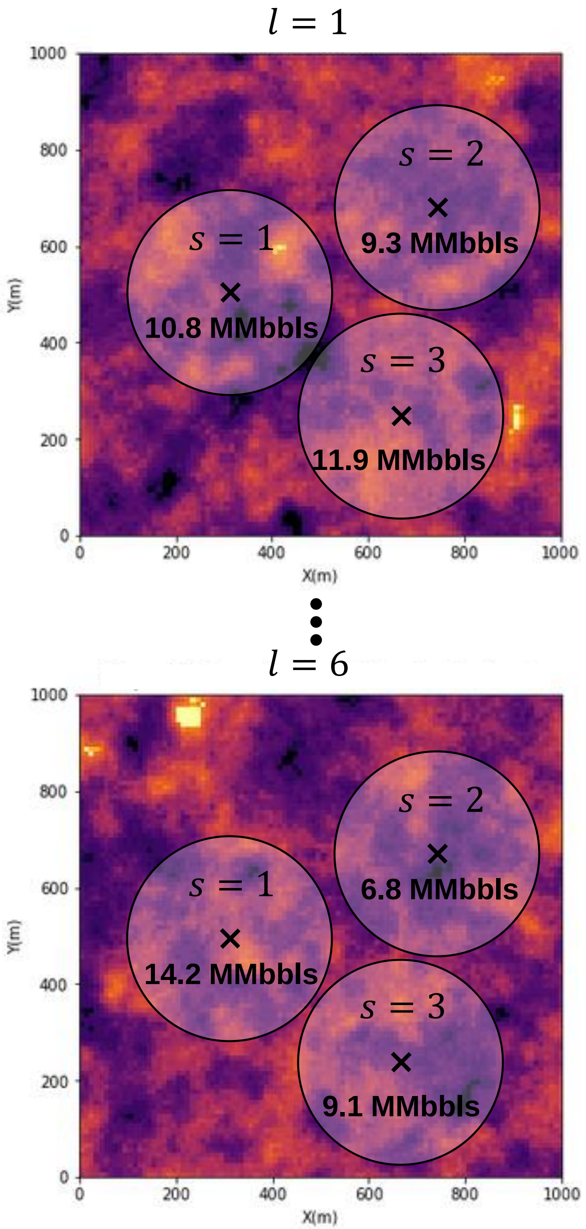
Decision Making by Maximizing Expected Value

Expected Profit Workflow:

1. Calculate the uncertainty model, $\boldsymbol{L}$ **subsurface realizations**
2. Establish $\boldsymbol{S}$ **development scenarios**
3. Establish $\boldsymbol{P}$ **profit metric**
4. Calculate profit, $\boldsymbol{P}$, over all $\boldsymbol{L}$ and $\boldsymbol{S}$

Repeat the calculation over all $\boldsymbol{L}$ and $\boldsymbol{S}$

- **Full combinatorial** of L subsurface realizations and S development scenarios, $\boldsymbol{P}(\boldsymbol{l}=\mathbf{1},\dots,\boldsymbol{L},\boldsymbol{s}=\mathbf{1},\dots,\boldsymbol{S})$



Profit calculated over all subsurface realizations and development scenarios.

Decision Making by Maximizing Expected Value

Expected Profit Workflow:

1. Calculate the uncertainty model, $\boldsymbol{L}$ **subsurface realizations**
2. Establish $\boldsymbol{S}$ **development scenarios**
3. Establish $\boldsymbol{P}$ **profit metric**
4. Calculate profit, $\boldsymbol{P}$, over all $\boldsymbol{L}$ and $\boldsymbol{S}$
5. Calculate the **expected profit** for each development scenario, $\boldsymbol{E\{P(S)\}}$

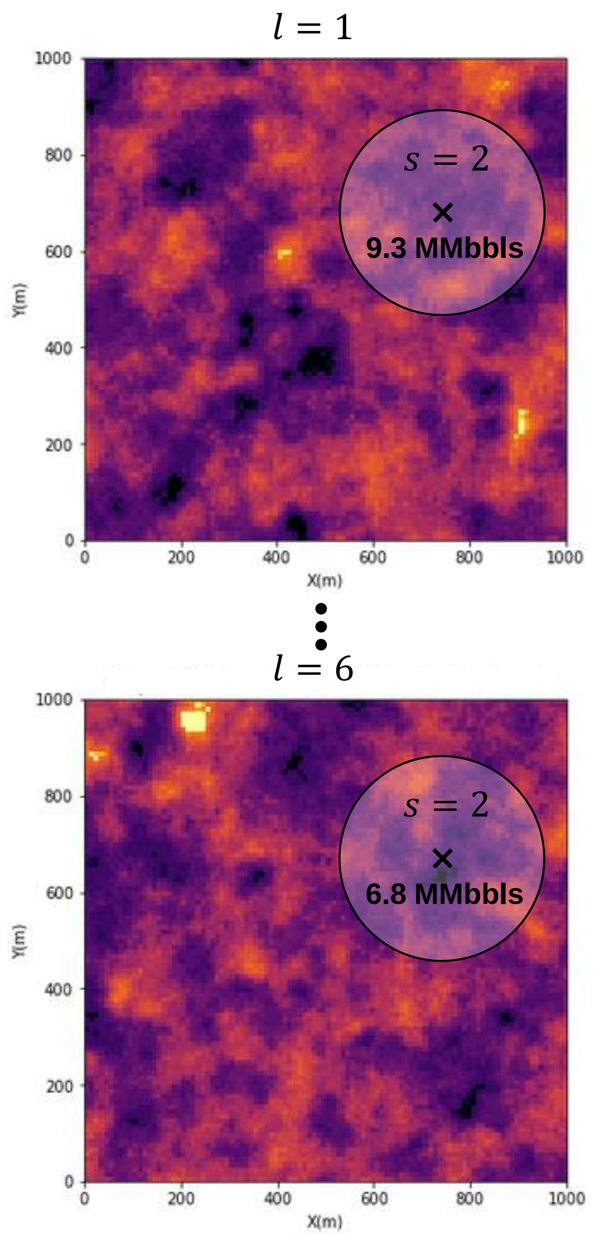
Calculation expected profit $\boldsymbol{E\{P(S)\}}$

- **Expected profit** is a probability, λ_l, weighted average of profit over subsurface uncertainty

$$\boldsymbol{E\{P(s=2)\}} = \frac{1}{\sum_{l=1}^{L} \lambda_l} \sum_{l=1}^{L} \lambda_l \cdot \boldsymbol{P(l, s=2)}$$

- if all models are equiprobable:

$$\lambda_l = \frac{1}{L}, l = 1, \ldots, L$$

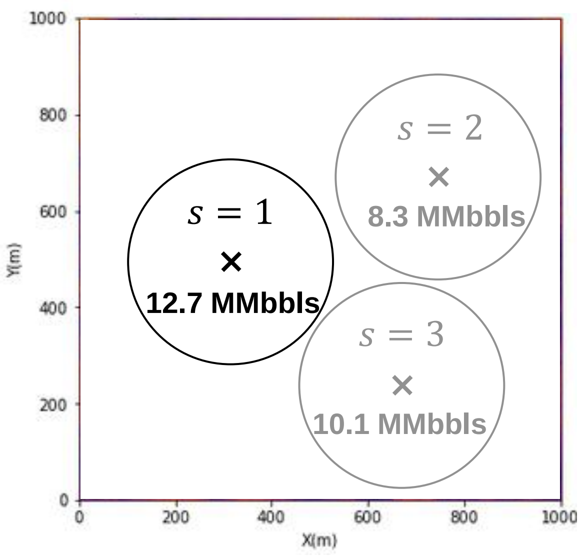


Expected profit calculated over all subsurface realizations.

Decision Making by Maximizing Expected Value

Expected Profit Workflow:

1. Calculate the uncertainty model, $\boldsymbol{L}$ **subsurface realizations**
2. Establish $\boldsymbol{S}$ **development scenarios**
3. Establish $\boldsymbol{P}$ **profit metric**
4. Calculate profit, $\boldsymbol{P}$, over all $\boldsymbol{L}$ and $\boldsymbol{S}$
5. Calculate the **expected profit** for each development scenario, $\boldsymbol{E\{P(S)\}}$
6. Select the s development scenario that **maximizes expected profit.**



$s = 1, \ldots, 3$ development scenarios with, $s = 1$ selected.

Maximize the expected profit $\boldsymbol{E\{P(S)\}}$

- **Select the development scenario** that maximizes expected profit over the subsurface realizations, $\boldsymbol{L}$

$$\boldsymbol{s = argmax(E\{P(S)\})}$$

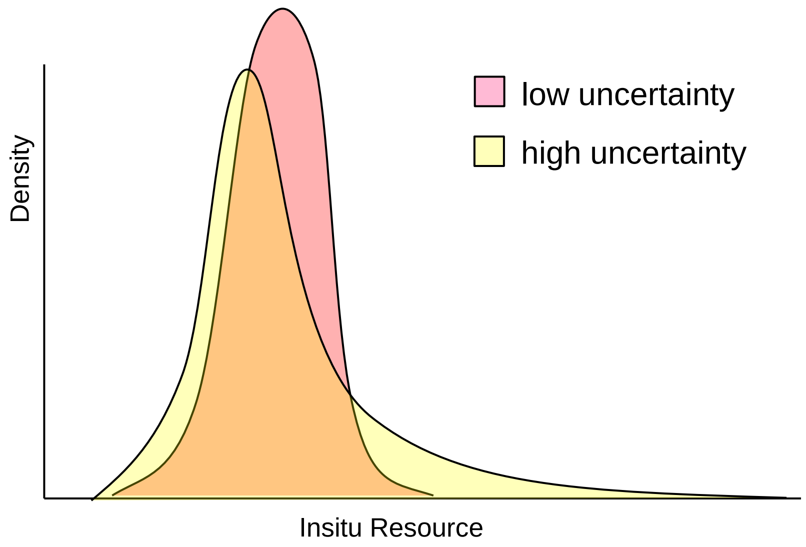
Decision Making
Impact of Uncertainty

What Uncertainty Distribution is Best?

Is narrower variance better?

- Higher variance may have more downside risk but also more upside potential.
- e.g., in shale play well product has a high variance, lognormal distribution and there are large well counts
  - a few high production wells can pay for the operation

- metal grades may also be approximately lognormally distributed
  - a small proportion of selective mining units impact the entire operation

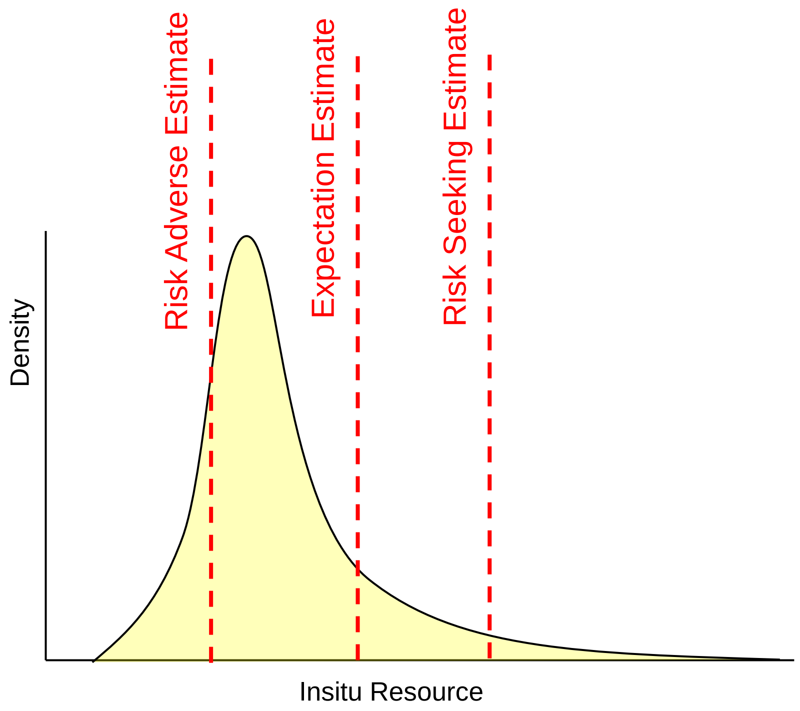


Two insitu resource uncertainty models

Optimum Estimates in the Presence of Uncertainty

How do we make optimum estimates in the presence of uncertainty?

- We cannot provide an uncertainty distribution to operations for decision making.
- **We must provide a single estimate.** We must choose a single estimate in the presence of uncertainty
- The **expectation estimate** (arithmetic average) assumes the cost of under- and over-estimation is symmetric and squared (L2 norm)
- **Risk Adverse** – cost of overestimation > cost of underestimation
- **Risk Seeking** – cost of overestimation < cost of underestimation
- Let's formalize this with the concept of **Loss Functions**.



Insitu resource uncertainty model and optimum decisions for risk-adverse, balanced (expectation) and risk-seeking.

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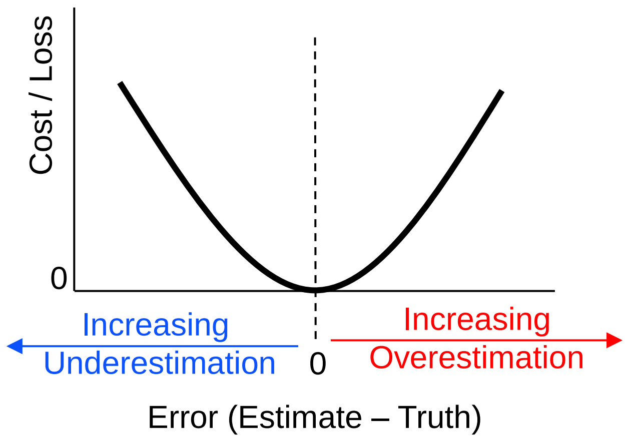
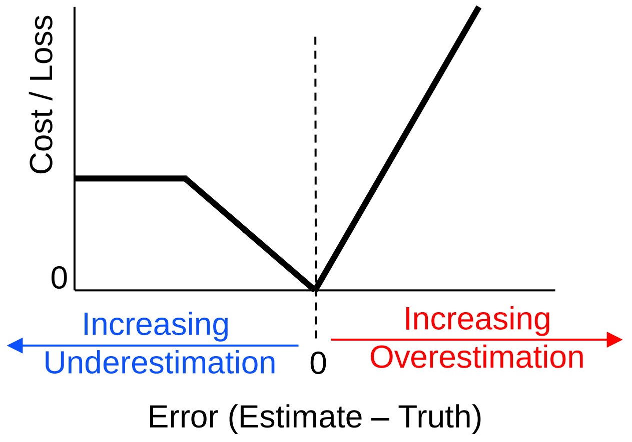
Decision Making With Uncertainty

Loss Functions

- To make a decision in the presence of uncertainty we need to quantify the loss function
- Loss due to over- and underestimation of the true value.
  - No loss if the estimate is correct, Estimate – Truth = 0
- Note: estimating with the mean minimizes the quadratic loss function
- For a more complicated example, overestimation is more costly than underestimation and at some threshold underestimation any further has no more cost.



Simple loss function, the cost of estimation error represented with a symmetric quadratic function.



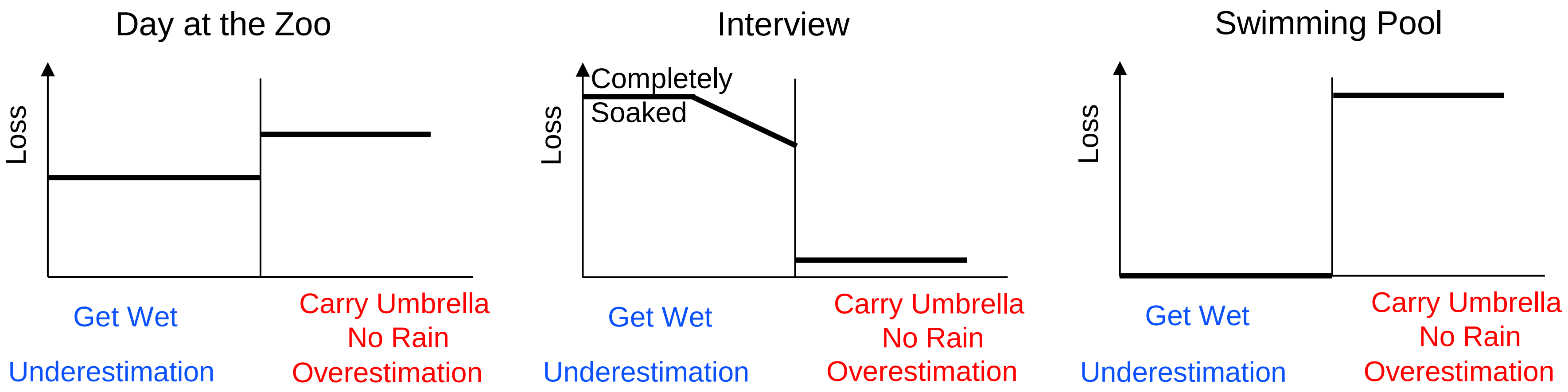
Complicated loss function, the cost of estimation error with asymmetry and thresholds.

Loss Function Example

- Loss function example to support the decision to carry an umbrella

Overestimation = you estimate rain, but no rain happens
Underestimation = you estimate no rain, but rain happens

- Should you carry an umbrella? The loss function depend on where you are going?



Loss functions for estimating rain for going to the zoo, an interview and the swimming pool.

Decision Making With Uncertainty

Decision Making in the Presence of Uncertainty :

- quantify cost of over and underestimation in a loss function
- apply loss function to the random variable of interest for a range of estimates
- calculate the expected loss for each estimate

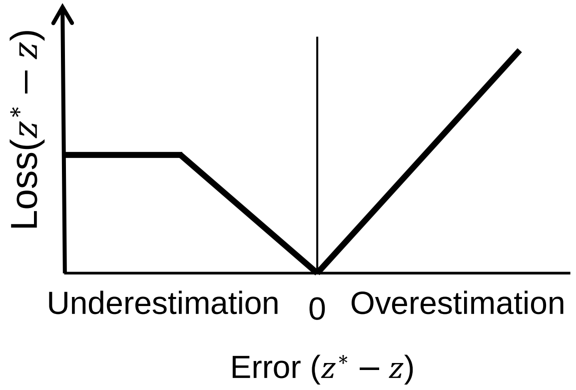
flipped

$$E\{Loss(z^*)\} = \int_{-\infty}^{\infty} Loss(z - z^*) \cdot f_z(z)\, dz$$

Loss for a specific amount of error

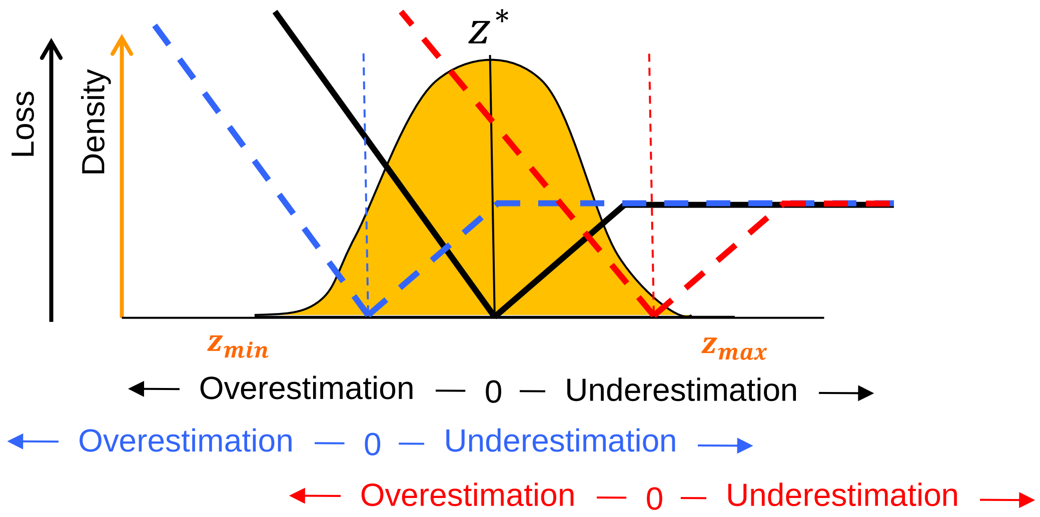
Probability of that error

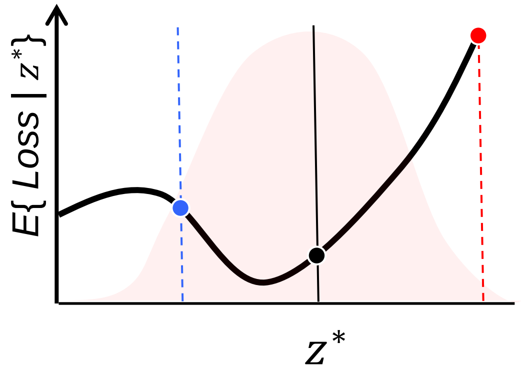
- make decision that minimizes loss



Loss function, function for cost of error.

Uncertainty PDF and Loss for 3 Estimate Cases





Schematic of expected loss calculation for 3 estimate cases.

Decision Making With Uncertainty

Expected Loss Calculation:

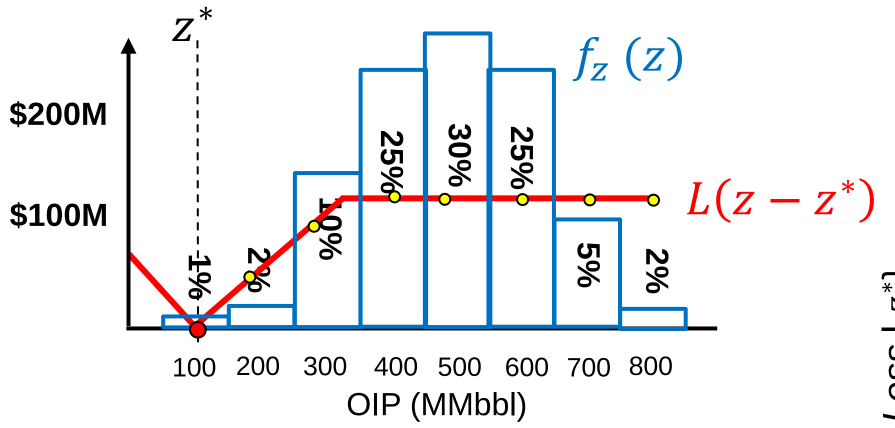
- Recall, expectation is a probability weighted average
- Calculation of the expected loss for a single estimate: $E\{Loss(z^*)\}$

$$E\{Loss(z^*\} = \int_{-\infty}^{\infty} L(z - z^*) \cdot f_z(z)\,dz = \underline{\sum L(z - z^*) \cdot P(z)}$$

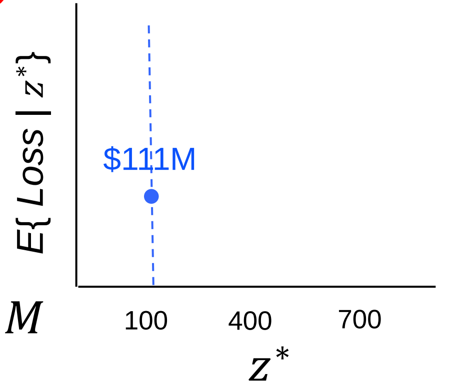
discrete approximation

Recall expectation is a probability weighted average.

$$E\{z\} = \int_{-\infty}^{\infty} z \cdot f_z(z)\,dz$$



$$E\{Loss(z^* = 100\ MMbbl)\} = \sum \text{1\% x \$0M} \quad \text{2\% x \$50M} \quad \text{10\% x \$100M} \quad \text{25\% x \$115M} \quad \text{30\% x \$115M} \quad \text{25\% x \$115M} \quad \text{5\% x \$115M} \quad \text{2\% x \$115M} = \$111M$$



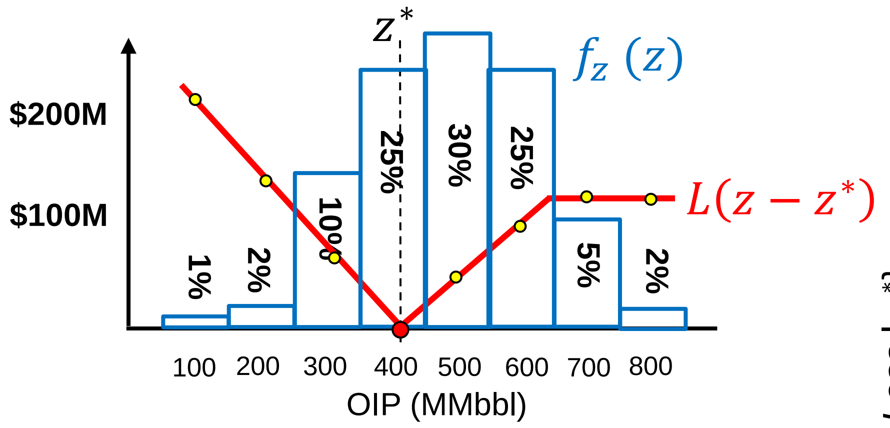
Expected Loss vs. estimate.

Decision Making With Uncertainty

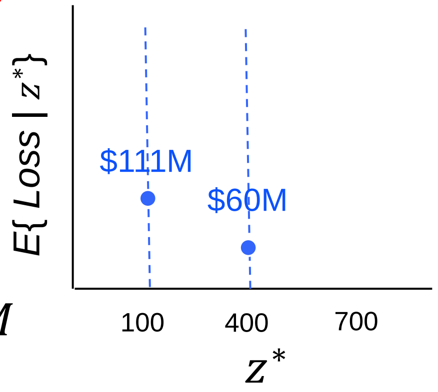
Expected Loss Calculation:

- Recall, expectation is a probability weighted average
- Calculation of the expected loss for a single estimate: $E\{Loss(z^*)\}$

$$E\{Loss(z^*\} = \int_{-\infty}^{\infty} L(z - z^*) \cdot f_z(z)\, dz = \underbrace{\sum L(z - z^*) \cdot P(z)}_{\text{discrete approximation}}$$



$$E\{Loss(z^* = 400\ MMbbl)\} = \sum \; 1\% \times \$210M \;\; 2\% \times \$140M \;\; 10\% \times \$70M \;\; 25\% \times \$0M \;\; 30\% \times \$50M \;\; 25\% \times \$100M \;\; 5\% \times \$115M \;\; 2\% \times \$115M \; = \$60M$$



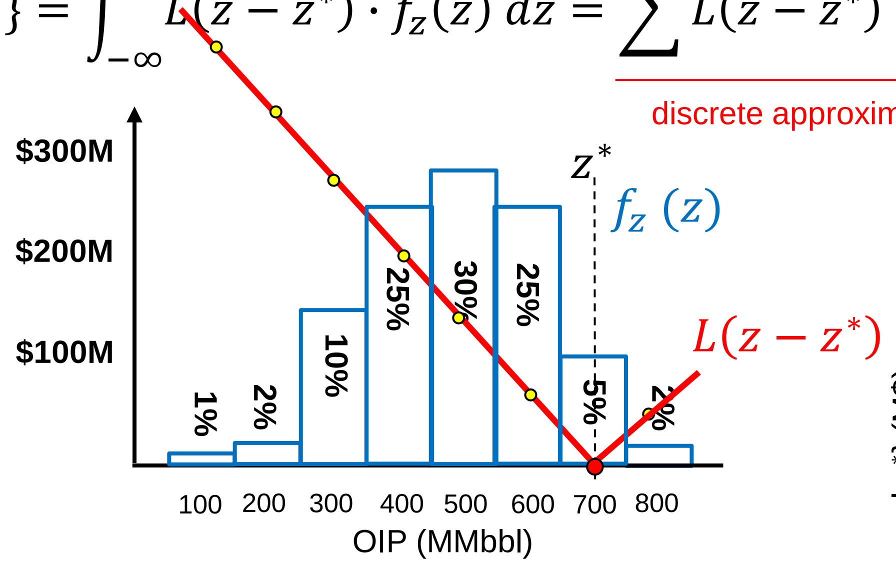
Expected Loss vs. estimate.

Decision Making With Uncertainty

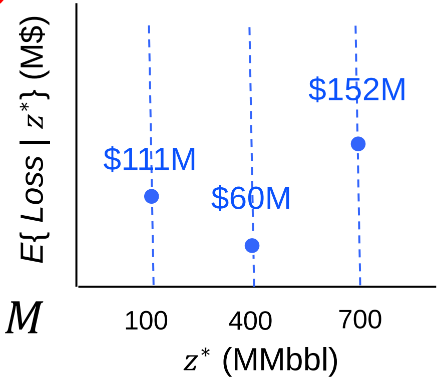
Expected Loss Calculation:

- Recall, expectation is a probability weighted average
- Calculation of the expected loss for a single estimate: $E\{Loss(z^*)\}$

$$E\{Loss(z^*\} = \int_{-\infty}^{\infty} L(z - z^*) \cdot f_z(z)\, dz = \underbrace{\sum L(z - z^*) \cdot P(z)}_{\text{discrete approximation}}$$



$$E\{Loss(z^* = 700\ MMbbl)\} = \sum \begin{matrix} 1\% \times \$420k \\ 2\% \times \$350k \\ 10\% \times \$280k \\ 25\% \times \$210k \\ 30\% \times \$140k \\ 25\% \times \$70k \\ 5\% \times \$0k \\ 2\% \times \$50k \end{matrix} = \$152M$$



Expected Loss vs. estimate.

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Lecture outline . . .

- Decision Making Example

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Decision Making With Uncertainty Example

Srivastava (1990) provided a great intuitive example for decision making in the precense of uncertainty:

- How much solvent should we inject to assist sweeping oil?
- Depends on connected volume, Mohan built 500 indicator realizations of sand / shale.
- Calculated the connected pore volume for each.

■ Shale

□ Sand

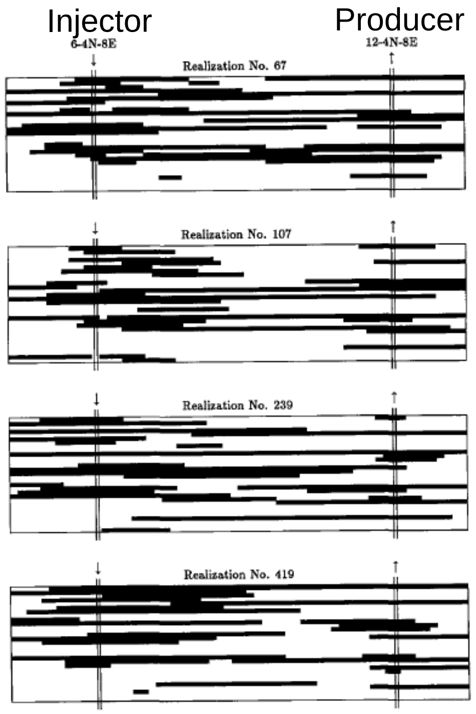


Fig. 3—Local detail for four of the 500 realizations.

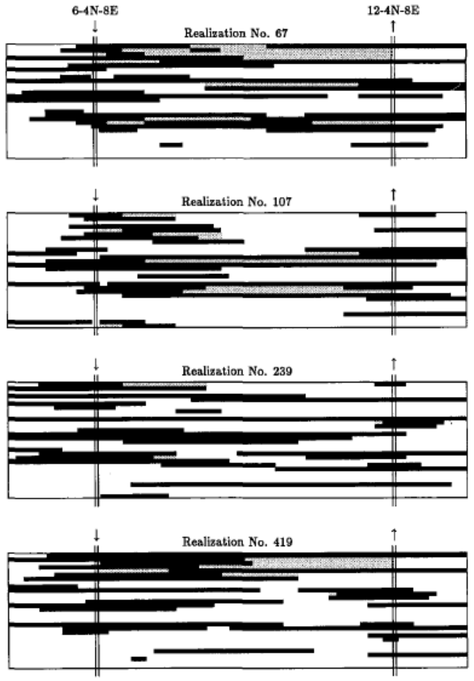


Fig. 4—Connected pore volume for the realizations shown in Fig. 3.

■ Shale

Disconnected sand

□ Connected sand

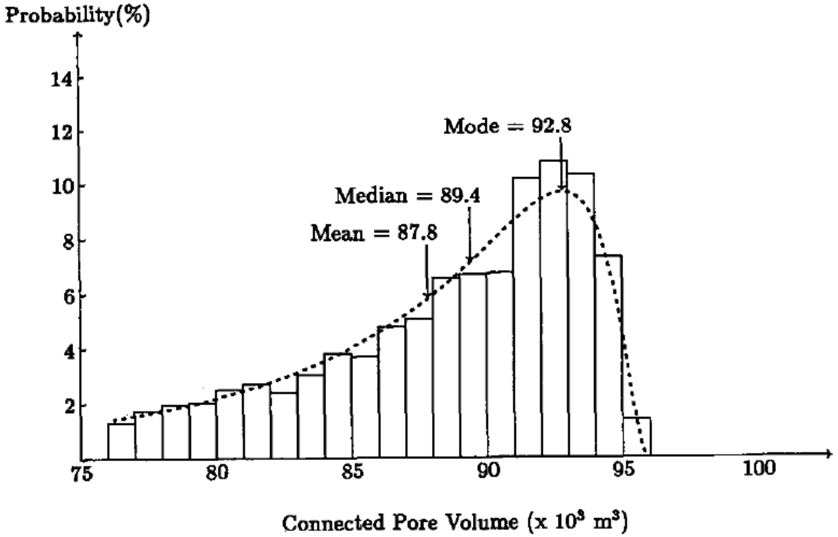
Injector and producer with four realizations of sand and shale (left) and disconnected sand indicated (right).

Image modified from Srivastava, 1990, 'An Application of Geostatistical Methods for Risk Analysis in Reservoir Management', Society of Petroleum Engineers, SPE# 20608

Decision Making With Uncertainty Example

Srivastava (1990) provided a great, intuitive example:

- From the 500 sequential indicator simulation realizations, we get this distribution of connected pore volume.



Uncertainty distribution for connected pore volume with summary statistics.

- But we have to decide on a specific volume of solvent treatment.
- We need a single estimate of pore volume!
  - This would depend on the risk associated with under- and overestimation of pore volume

    we use a loss function to model this

Image from Srivastava, 1990, 'An Application of Geostatistical Methods for Risk Analysis in Reservoir Management', Society of Petroleum Engineers, SPE# 20608

Decision Making With Uncertainty Example

Srivastava (1990) provided a great, intuitive example:

- The loss function is asymmetric as a function of error in connected pore volume ‘X’ m^3 :

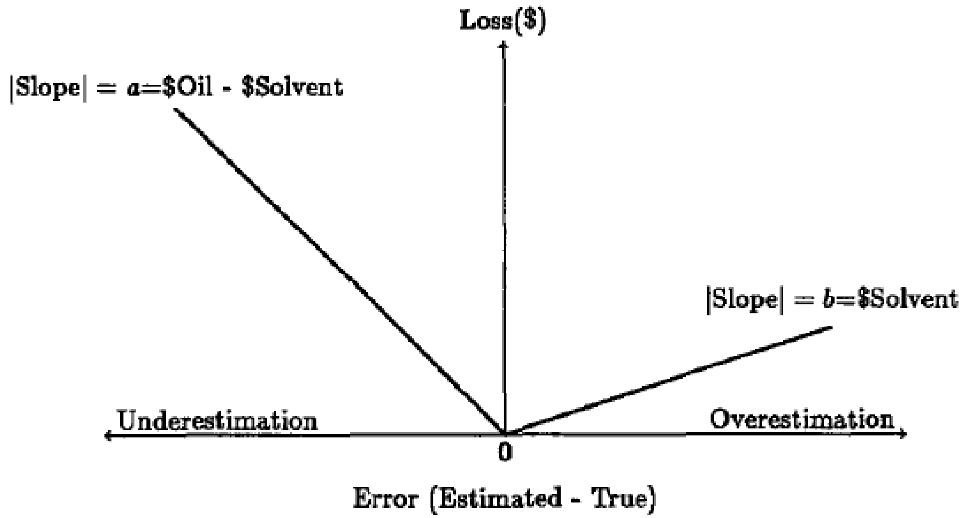
Overestimate by ‘X’ m^3, waste that solvent, cost of solvent

‘X’ m^3 **x solvent cost$ /** m^3

Underestimate by ‘X’ m^3, leave ‘X’ m^3 Oil behind, but save on solvent

‘X’ m^3 **x price of oil$ /** m^3 - ‘X’ m^3 **x solvent cost$ /** m^3

Loss function depends on cost of solvent and price of oil.



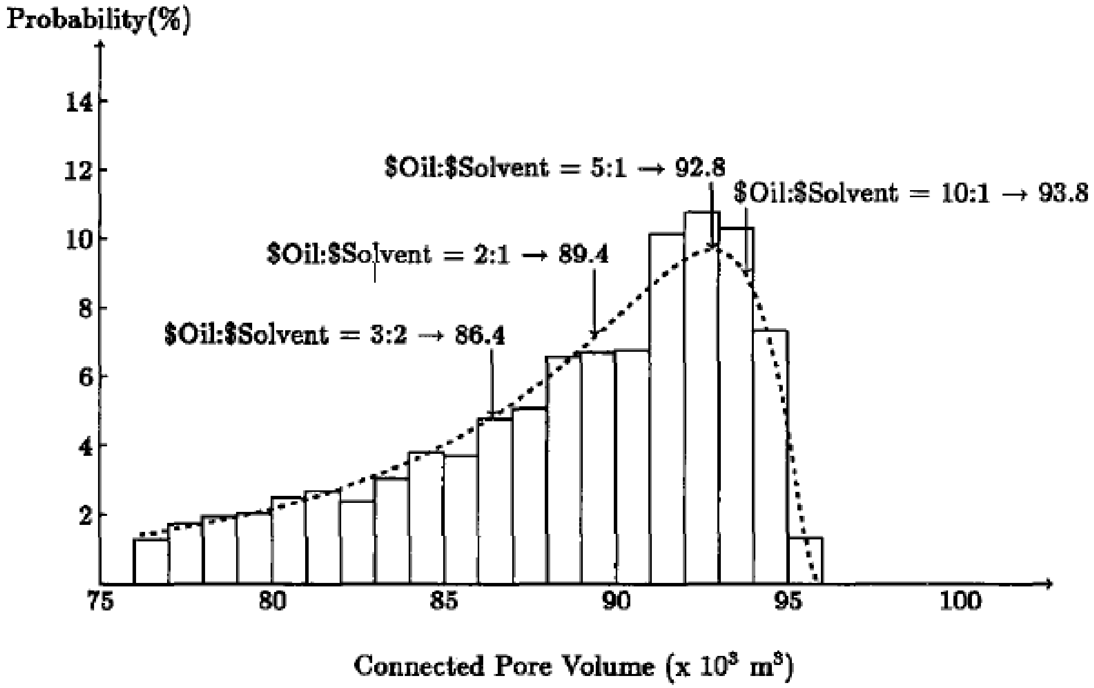
Asymmetric, linear loss function.

Image from Srivastava, 1990, ‘An Application of Geostatistical Methods for Risk Analysis in Reservoir Management’, Society of Petroleum Engineers, SPE# 20608

Decision Making With Uncertainty Example

Srivastava (1990) provided a great intuitive example:

- Applying the loss function to the uncertainty distribution and select the pore volume estimate that minimizes the expected loss.
- The best estimate of the pore volume depends on the ratio of the price of oil to the cost of solvent.



Uncertainty distribution for connected pore volume with optimum estimate for Oil:Solvent cost ratios.

Image from Srivastava, 1990, 'An Application of Geostatistical Methods for Risk Analysis in Reservoir Management', Society of Petroleum Engineers, SPE# 20608

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Decision Making With Uncertainty Hands-on

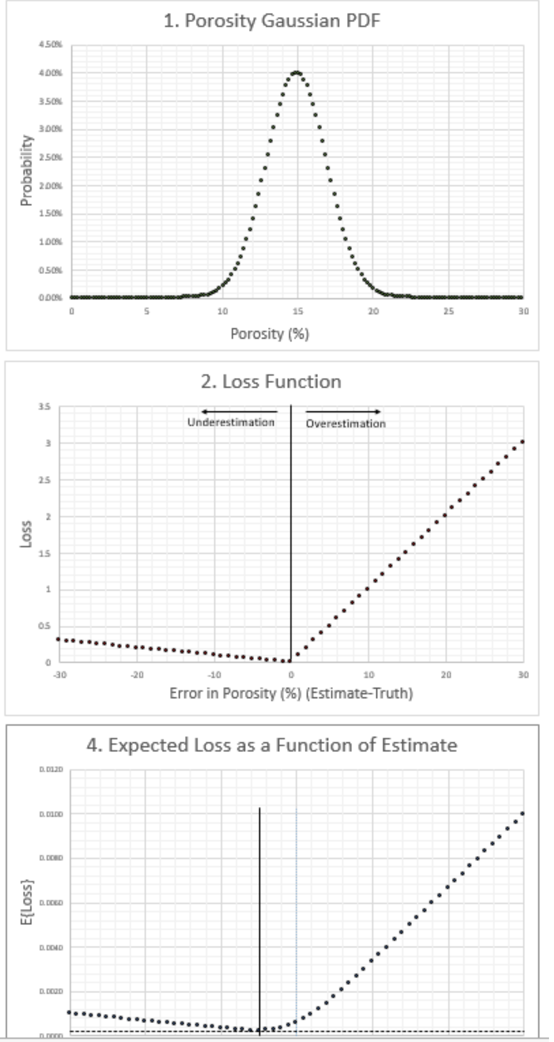
Things to Try Out:

- Try increasing and decreasing the cost of overestimation and observe the estimate.
- Try increasing and decreasing the standard deviation of the uncertainty model.
- Try asymmetric loss functions.

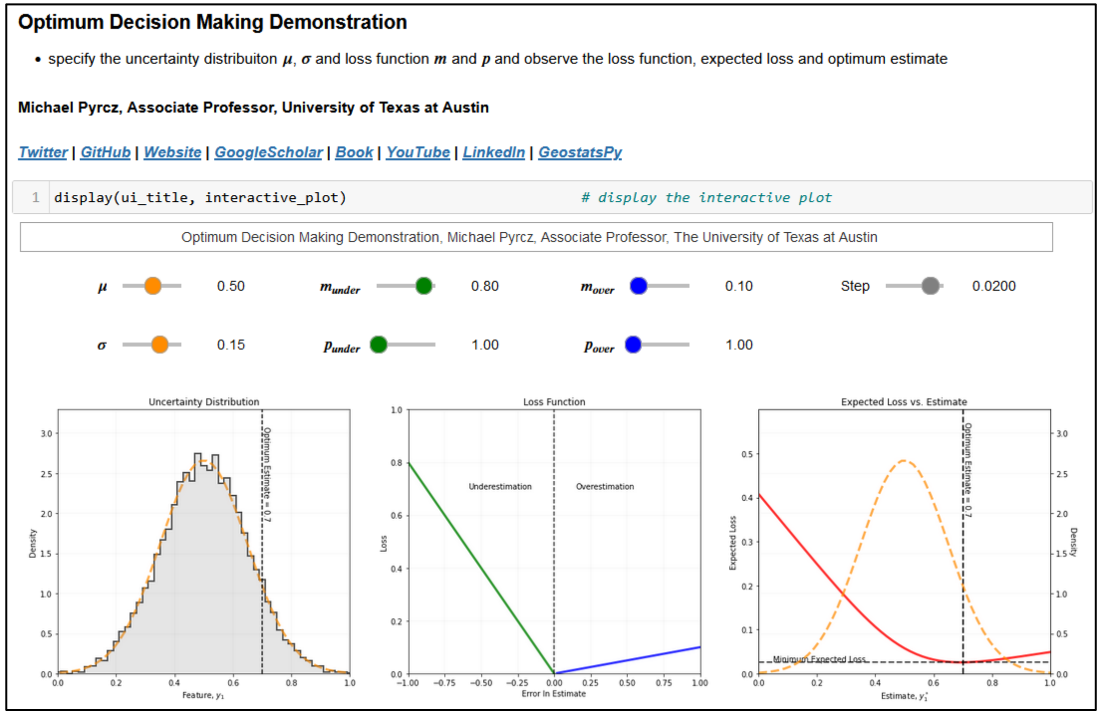
The File is Decision_Making_with_Loss_Function.xlsx at https://git.io/fNgBx.

1. Gaussian Distribution Parameters		
Mean	15	
Standard Deviation	2	

Porosity (%)	Probability	Probability Normalized
0.1	1.8E-13	0.00%
0.3	3.7E-13	0.00%
0.5	7.7E-13	0.00%
0.7	1.6E-12	0.00%
0.9	3.2E-12	0.00%
1.1	6.5E-12	0.00%
1.3	1.3E-11	0.00%
1.5	2.5E-11	0.00%
1.7	5.0E-11	0.00%
1.9	9.6E-11	0.00%
2.1	1.8E-10	0.00%
2.3	3.5E-10	0.00%
2.5	6.6E-10	0.00%
2.7	1.2E-09	0.00%
2.9	2.2E-09	0.00%
3.1	4.1E-09	0.00%
3.3	7.4E-09	0.00%
3.5	1.3E-08	0.00%
3.7	2.3E-08	0.00%
3.9	4.1E-08	0.00%
4.1	7.1E-08	0.00%
4.3	1.2E-07	0.00%
4.5	2.1E-07	0.00%
4.7	3.5E-07	0.00%
4.9	5.8E-07	0.00%
5.1	9.5E-07	0.00%
5.3	1.6E-06	0.00%
5.5	2.5E-06	0.00%
5.7	4.0E-06	0.00%
5.9	6.4E-06	0.00%
6.1	1.0E-05	0.00%
6.3	1.6E-05	0.00%
6.5	2.4E-05	0.00%
6.7	3.6E-05	0.00%
6.9	5.5E-05	0.00%
7.1	8.2E-05	0.00%
7.3	1.2E-04	0.00%
7.5	1.8E-04	0.00%
7.7	2.6E-04	0.01%
7.9	3.7E-04	0.01%
8.1	5.2E-04	0.01%
8.3	7.3E-04	0.01%
8.5	1.0E-03	0.02%
8.7	1.4E-03	0.03%
8.9	1.9E-03	0.04%
9.1	2.6E-03	0.05%
9.3	3.4E-03	0.07%
9.5	4.5E-03	0.09%
9.7	6.0E-03	0.12%
9.9	7.7E-03	0.15%
10.1	9.9E-03	0.20%
10.3	1.3E-02	0.25%
10.5	1.6E-02	0.32%
10.7	2.0E-02	0.40%
10.9	2.4E-02	0.49%
11.1	3.0E-02	0.60%
11.3	3.6E-02	0.72%
11.5	4.3E-02	0.86%
11.7	5.1E-02	1.02%
11.9	6.0E-02	1.20%
12.1	7.0E-02	1.39%
12.3	8.0E-02	1.60%
12.5	9.1E-02	1.83%
12.7	1.0E-01	2.06%
12.9	1.1E-01	2.30%
13.1	1.3E-01	2.54%



Decision Making With Uncertainty Interactive Python



The File is Interactive_DecisionMaking.ipynb.

Things to Try Out:

- Try increasing and decreasing the cost of overestimation and observe the estimate.
- Try increasing and decreasing the standard deviation of the uncertainty model.
- Try asymmetric and nonlinear loss functions.

PGE 338 Data Analytics and Geostatistics

Lecture 16c: Decision Making

Lecture outline . . .

- Decision Making
- Loss Functions
- Decision Making Example
- Decision Making Hands-on

Michael Pyrcz, The University of Texas at Austin

Introduction

General Concepts

Univariate

Bivariate

Spatial

Calculation

Variogram Modeling

Kriging

Simulation

Time Series

Machine Learning

Uncertainty Analysis

Decision Making with Uncertainty New Tools

Topic	Application to Subsurface Modeling
Joint Optimal vs. L Suboptimal Selection	Find the choice that maximizes the expected profit over all models, cannot work with a few or a single model! *This choice will not maximize profit for any given geological model.*
Decision Making with Uncertainty	*We can solve for the development scenario that maximizes expected profit over all geological realizations.* *Formulate a profit transfer function and apply it to the combinatorial of geological realizations and development scenarios.*
Estimating with Uncertainty	*The estimate from an uncertainty distribution for decision making depends on the cost of under and over estimation.* *Construct a loss function and determine the OIP estimate for a reservoir from the OIP uncertainty distribution accounting for the cost of under and over estimation of OIP.*