Week 3: Risk and Evaluation of Alternatives

- Making Decisions in Low-Uncertainty vs. High-Uncertainty Settings
- Example: Evaluating a Wireless Data Plan
- Reward and Risk

Session 1

- Connecting Random Inputs and Random Outputs
- Simulating Uncertain Outcomes in Excel

Session 2

- Interpreting Simulation Results: “Short” vs. “Long” Simulations
- Using Histograms to Visualize Simulation Results

Session 3

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Making Decisions in Low-Uncertainty vs. High-Uncertainty Settings

- In low-uncertainty settings, each particular **decision** produces a certain, non-random outcome, both in terms of
  - the **objective function value** (such as profit in the Zooter example or total shipping cost in the KDGL example)
  - other **key performance indicators** (such as resource consumption quantities in the Zooter example or shipped amounts for each warehouse and distribution center in the KDGL example)

- In the Zooter example, if the company decides to produce 500 Razor and 500 Navajo scooters, it will make a profit of exactly $155000 and will use up exactly 4500 frame manufacturing hours

Making Decisions in Low-Uncertainty vs. High-Uncertainty Settings

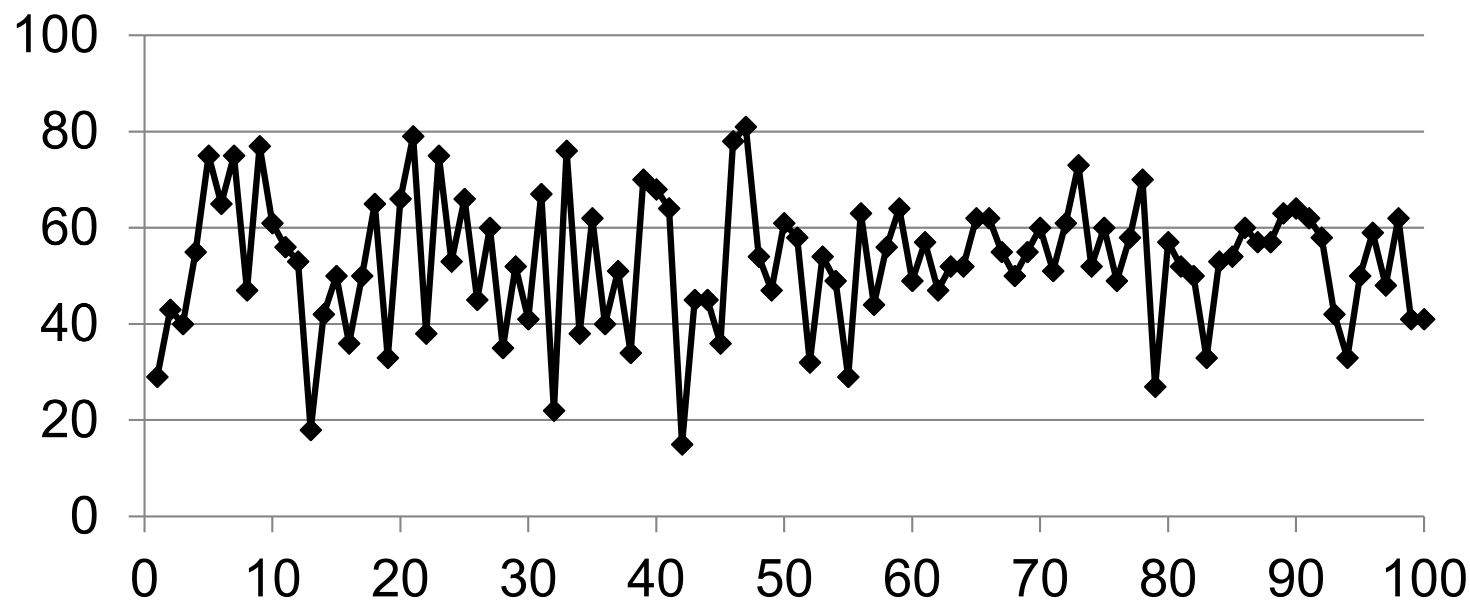
- Newsvendor example:
  - A product (*Wodget*) sells for price of 12 talers
  - The cost of the product is 3 talers
  - If an item is unsold, it has to be salvaged at no value (i.e. sold for 0 talers)

- In a high-uncertainty environment (such as the newsvendor example) a decision (such as the choice of a particular value for the inventory of a fashion product, Q) must often be made before all the factors (such as the demand for the product, D) that impact the outcome (such as profit π) are known

- At the time when the inventory decision is made, the demand D is unknown, and can be modeled as a random variable

Modeling Random Variables using Scenarios

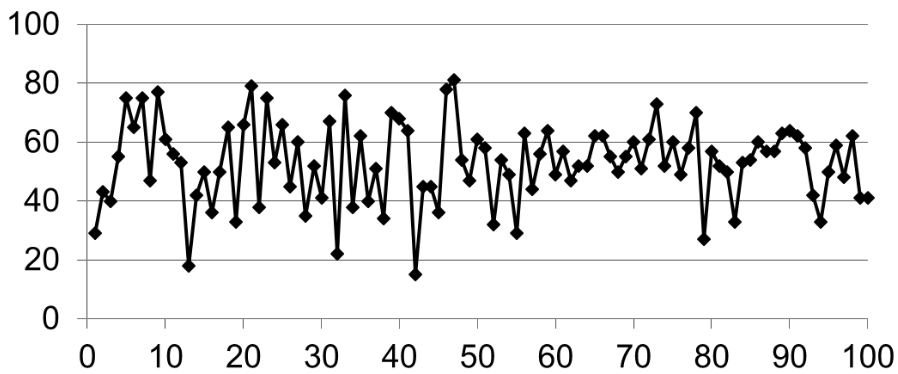
- Random variables can be modeled using a “scenario” approach
  - Each scenario is a value that a random variable can take
  - Each scenario has a probability of being realized

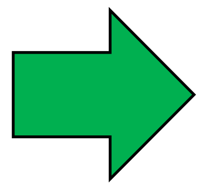


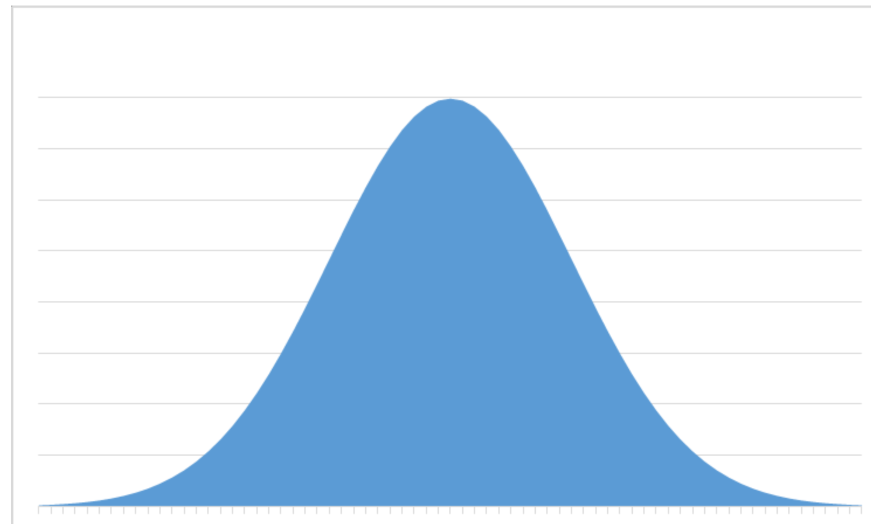
- For example, one can use historical data as scenarios for the future demand, with equal probabilities attached to each demand value observed in the past

Modeling Random Variables using Continuous Probability Distributions

- Or, one can “fit” a probability distribution (for example, a normal distribution) to historical data and use that distribution to model future demand

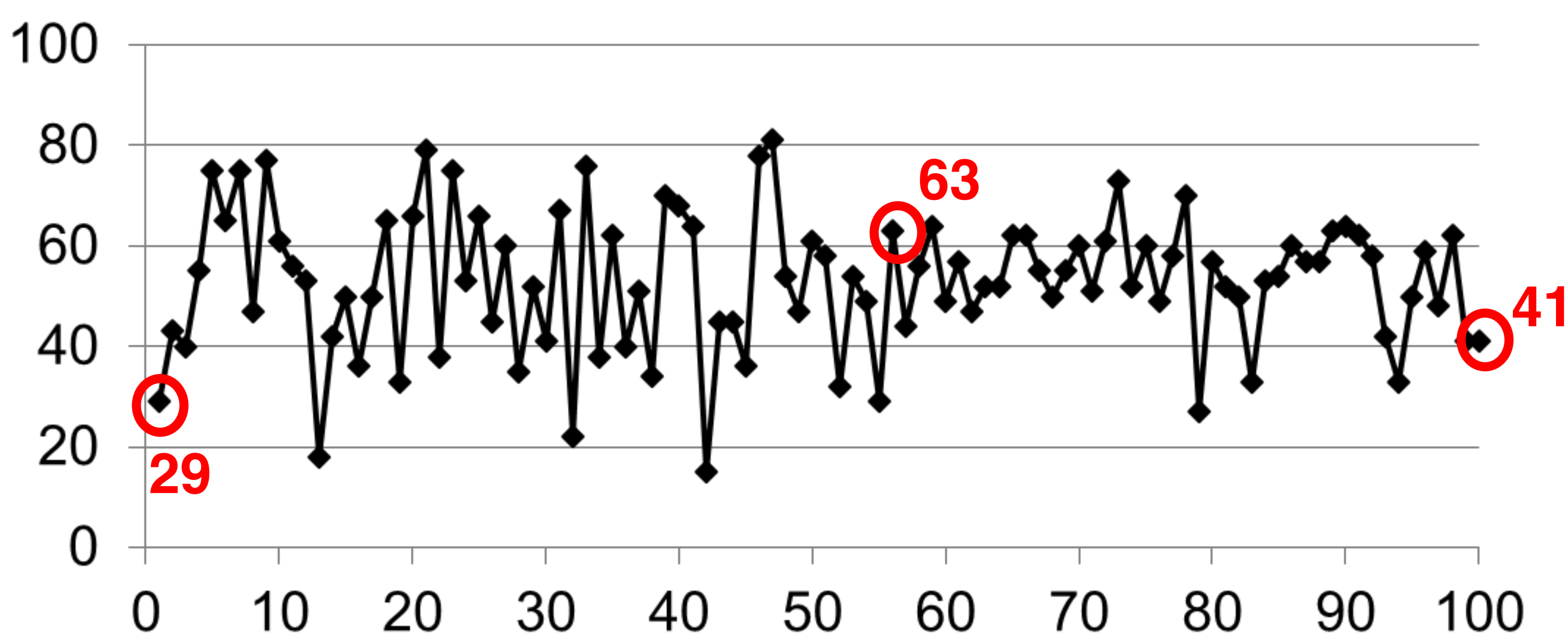






Random Demand May Lead to Random Profit

- If the demand is modeled as a random variable, profit π may also become a random variable
- Consider three demand values observed in the past



Random Demand May Lead to Random Profit

- If the demand is modeled as a random variable, profit π may also become a random variable.

- Let's say we decided to order Q=50 units of product "now"

Random Demand May Lead to Random Profit

- If the demand is modeled as a random variable, profit π may also become a random variable

"Now"	"Later"		
	$D = 29$	→	$\pi = 12*29-3*50 = 198$ talers
$Q=50$	$D = 63$	→	$\pi = 12*50-3*50 = 450$ talers
	$D = 41$	→	$\pi = 12*41-3*50 = 342$ talers

- A decision leads to a distribution of profits, rather than a certain, fixed profit value

Choosing Best Decisions

In Low-Uncertainty Settings

Week 3

- For each decision, we must calculate the objective function value and determine if the decision is feasible

$(R,N) \Rightarrow 150*R+160*N$

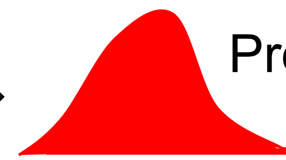
- Among all feasible decisions, we select one with the best objective function value

$\max\ 150*R+160*N$

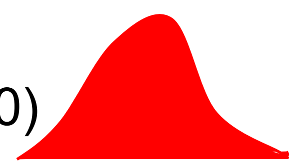
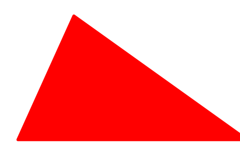
Week 4

In High-Uncertainty Settings

- For each decision, we must know how to calculate a distribution for any key performance indicator (such as profit, cost, resource utilization, etc.)

Q

Profit

- When choosing the best among different decisions, we must know how to compare distributions of outcomes

Profit (Q=50)

vs.

Profit (Q=70)

Example: Evaluating a Wireless Data Plan

- A business analytics consultant based in Philadelphia is considering changing her wireless data plan to accommodate her family's growing use of video streaming services
- Under her current data plan called "Family Share" she pays $10 for each GB of data her family uses in a given month
- After doing research on data plans offered by her wireless carrier, the consultant has decided to select the plan her carrier calls "Superior Share"
- Under the Superior Share plan, the consultant will pay a flat fee of $160 for up to 20GB of data per month. This data allowance may be shared among all members of her family

Example: Evaluating a Wireless Data Plan

- If her family's actual monthly data usage exceeds 20GB, she will then have to pay for any data usage above this threshold at the rate of $15 per GB
  - For example, if her family's monthly data usage is 22GB, her monthly payment will be $160+(22-20)*$15 = $190

- If her family's actual monthly data usage does not exceed 20GB, she will still have to pay the full $160 amount, and the amount of unused data under 20GB will not "roll over" to the next month
  - For example, if her family's monthly data usage is 17GB, her monthly payment will be $160

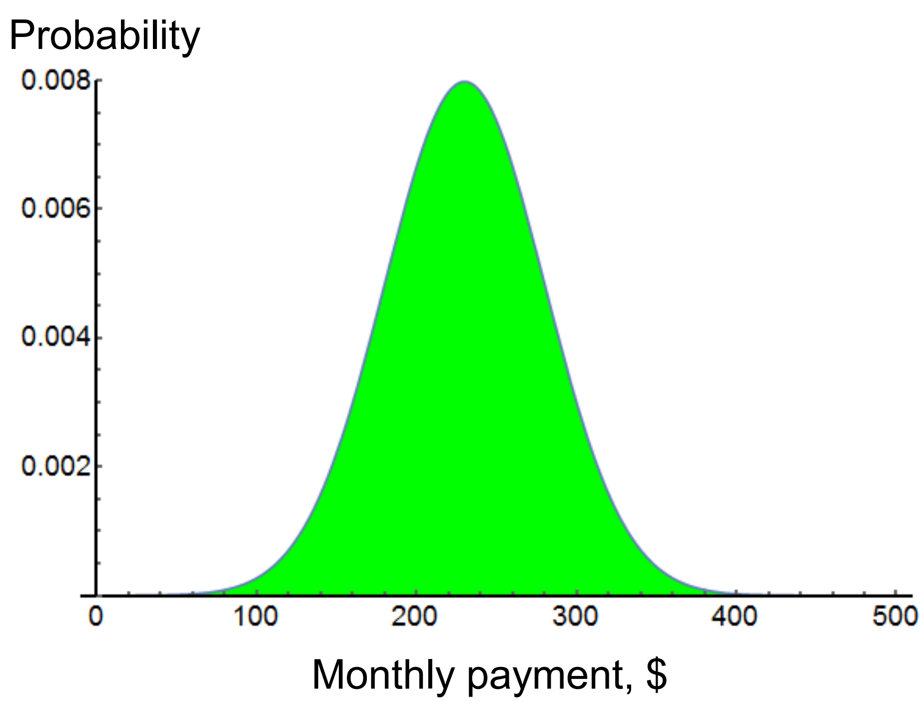
Key “Output” Measure: Monthly Payment

- The consultant worries about the actual **payment** she will incur under this data plan in a given month
- As the data plan stipulates, her actual **monthly payment** depends on the amount of her family’s **data usage** during that month
- At the time of her decision to purchase the plan, she does not know exactly what her family’s future data usage will be
- Predictive analytics provides a means to combine historical data on monthly data usage with expert judgement to come up with the probability distribution for future data usage

Monthly Payment Under Old Plan: Probability Distribution

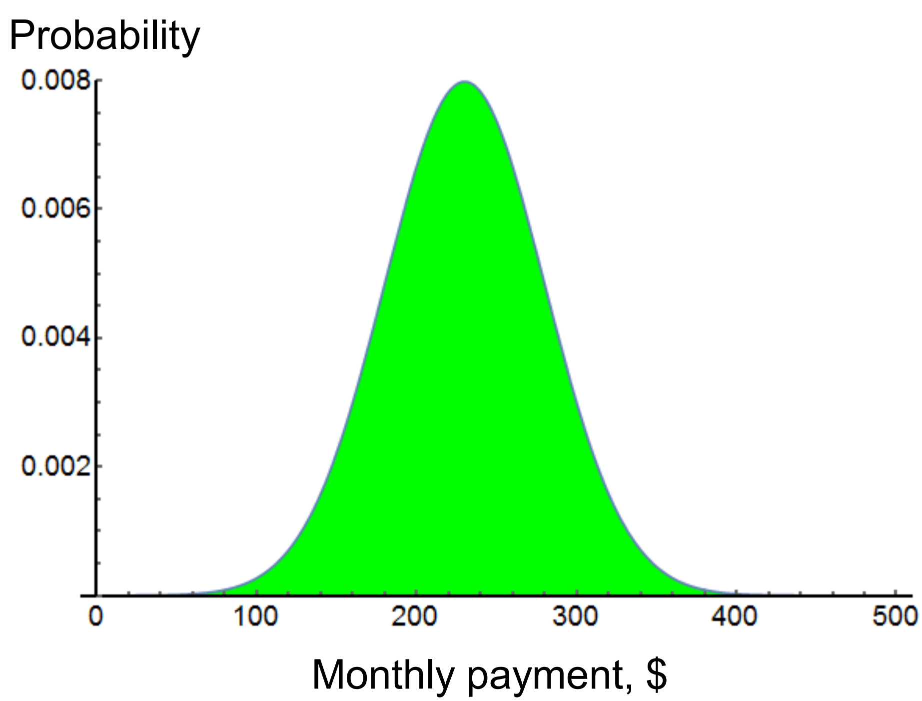
- Based on the analysis of her family's past monthly data usage values, the consultant decided to model data usage in any month as a **normal random variable with a mean of 23GB and a standard deviation of 5GB.**

- Then, if the consultant stays with her current data plan, her actual monthly payment is a normal random variable **with a mean of $230 and a standard deviation of $50**



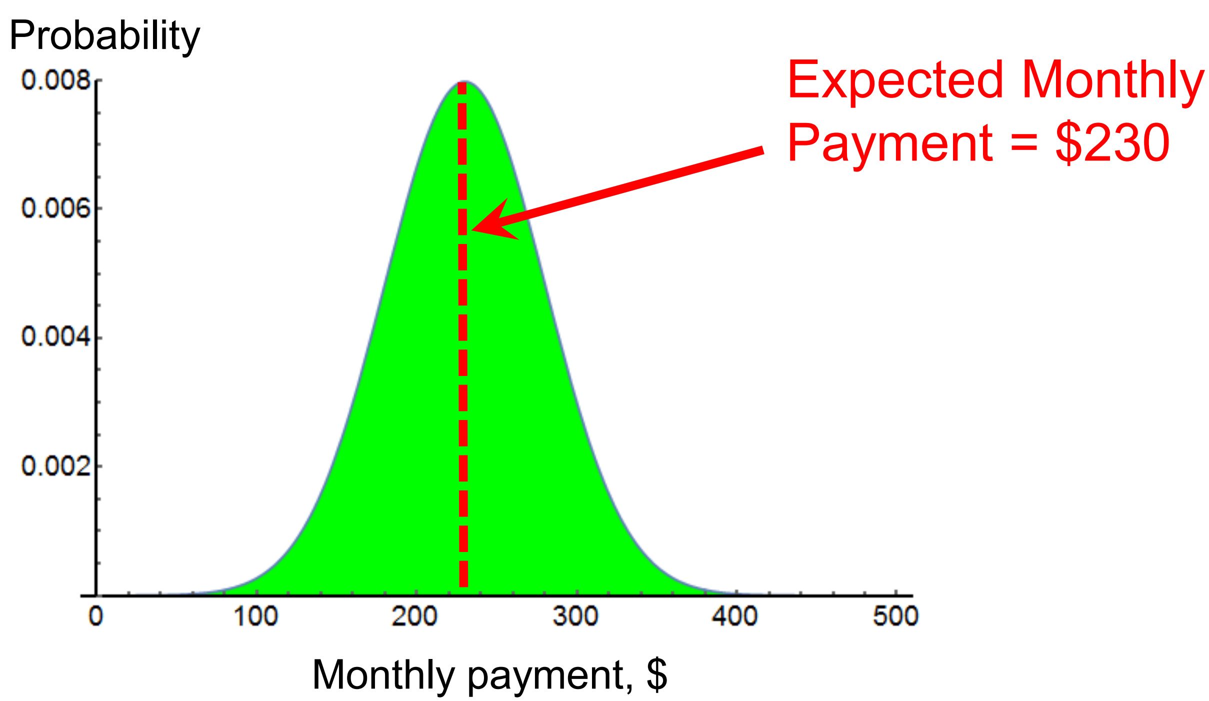
Reward and Risk

- In dealing with uncertain outcomes it may be important to be able to calculate **performance measures** that can be used to compare decisions, like decisions to choose a new data plan versus staying with the old one
- When comparing decisions under uncertainty, we can then use such performance measures as an **objective function** and **constraints**



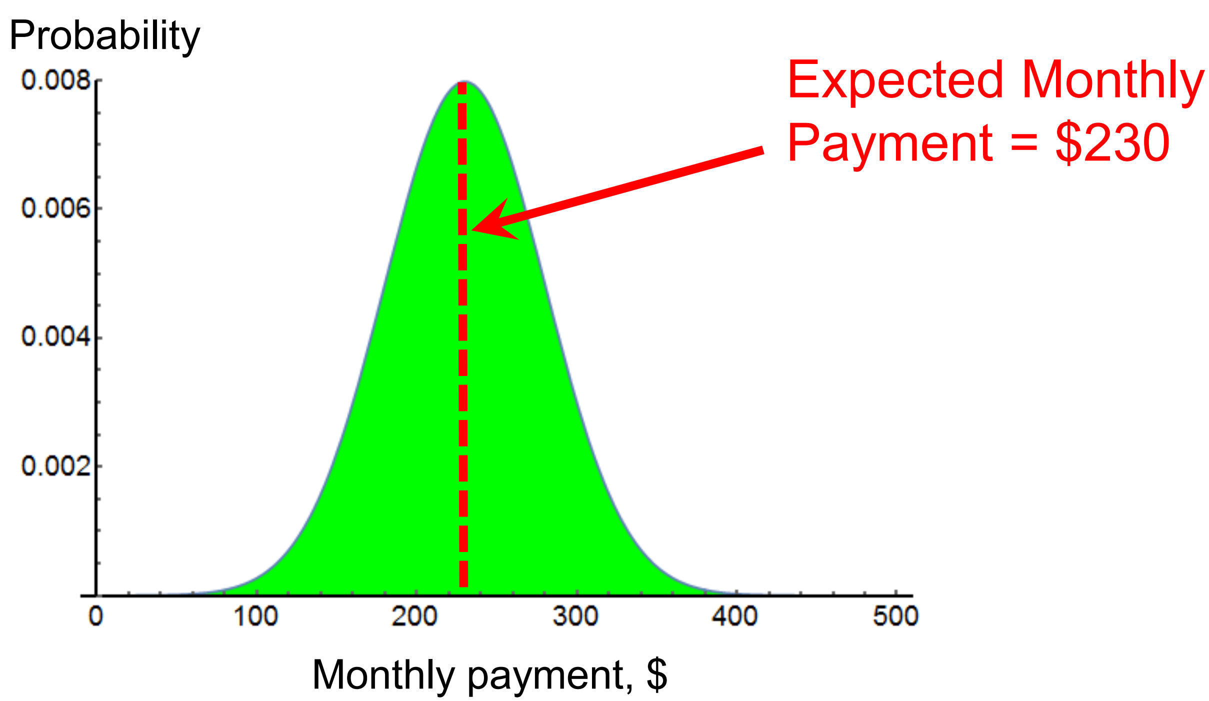
Reward and Risk

- One such performance measure is **“reward”**
- **Expected value of cost or profit** is often used as an indication of “attractiveness” of a particular decision
- Expected value of the monthly payment is what the consultant would pay, on average, if she would stay with her old data plan for an **infinite number of months**
- All other things being equal, a lower expected monthly payment is more attractive



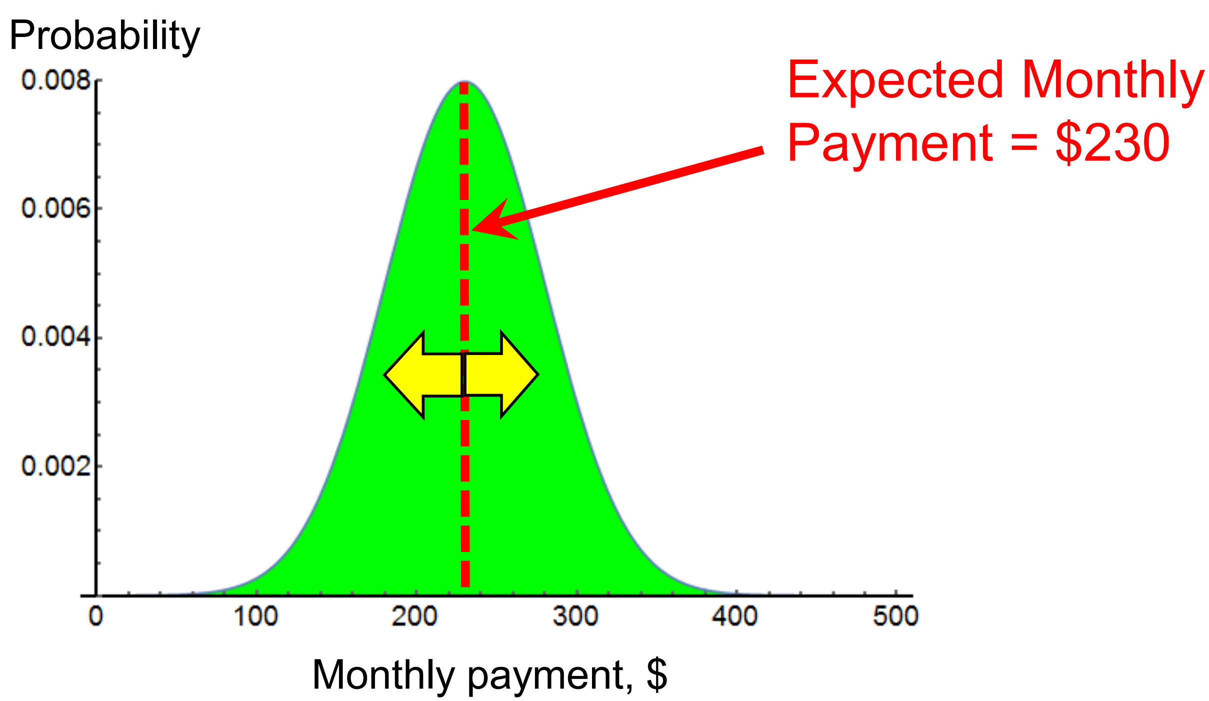
Reward and Risk

- The expected monthly payment is what the consultant would pay on average over infinite number of months
- But, in **any given month**, the actual monthly payment is uncertain and can be quite far away from the expected value of $230



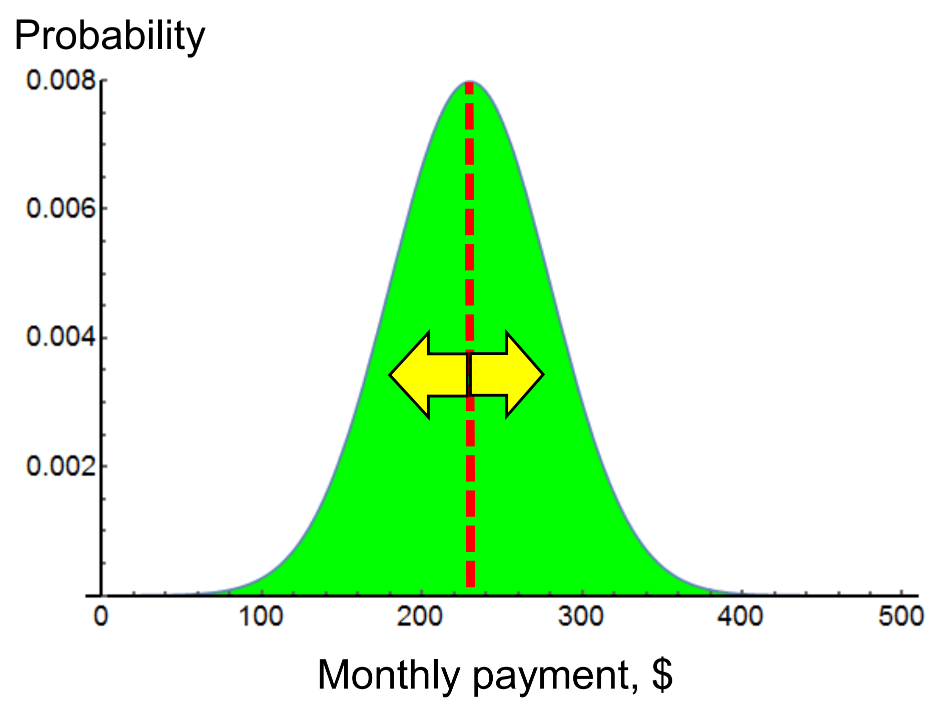
An Example of Risk Measure: Standard Deviation of Monthly Payments Under Old Data Plan

- The **standard deviation** expresses how far away a consultant should expect her actual monthly payment to be from the expected value of \$230
- Under the old data plan, the standard deviation of monthly payments is \$50
- All other things being equal, a smaller standard deviation may be more attractive



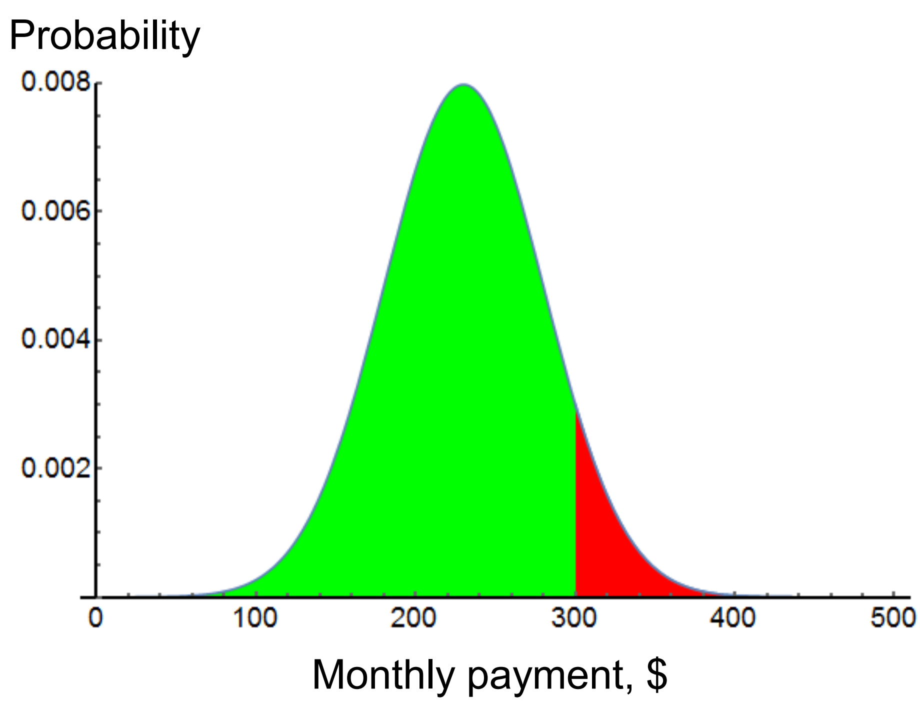
An Example of Risk Measure: Standard Deviation of Monthly Payments Under Old Data Plan

- What constitutes “risk” may be different for different decision makers
- Some may worry about the value of the standard deviation of monthly payments being too large



An Example of Risk Measure: Standard Deviation of Monthly Payments Under Old Data Plan

- What constitutes “risk” may be different for different decision makers
- Some may worry about the value of the standard deviation of monthly payments being too large
- Others may be concerned about the **likelihood of actual monthly payments reaching or exceeding a certain threshold**, e.g., $300



Making Best Decisions in High-Uncertainty Settings: A Roadmap

Decide upon **reward** and **risk** measures

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For each competing decision, use **simulation** to estimate reward and risk measures — **This week**

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Use **reward** as an **objective** and **risk measures** as **constraints** to find the best decision — **Next week**