

Lecture 1 : What's economics?

This class is for most of you your first introduction to the foundations of microeconomics. So, to help you gain a bird's eye view of microeconomics, I will first describe some concepts & terms.

A. models

Microeconomics is a collection of mathematically based models that describe narrow features of human behavior. Not exhaustive depictions — this is not a replacement of psychology, sociology, or any of the social science branches you can name. It's a narrow modeling, and I will explain to you its distinctiveness & explore it with you in the context of these models.

Models are unique objects. Depending on your background, & exposure to much screenap, you may find models to be very unusual. For instance, I may say things like "assuming people have transitive, continuous & complete preference ordering, then this model predicts they will buy more of something when its price rises so long as the substitution effect is smaller than the income effect." It's a strange way of talking, first of all, but even stranger maybe is the idea that I am making prediction about what a person will do in some situation all because I solved a ~~utility max~~ a simple constrained optimization

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problem — when I know "real people" don't solve optimization problems when they buy things. So part of this class is to teach you about the usefulness of theoretical models, and the usefulness of stories, even when those stories aren't exactly "true", per se.

Models are like maps. They are like them in purely a metaphorical way, I mean. Say that you go to Florence, Italy — an ancient city filled with history & culture. Maps are useful to you if you've never been there, but only if you have a certain purpose. If your goal is to see all the cathedrals, for instance, then a spatial map showing the locations is about what you need. But what if you are wanting a history tour experience? What if you are an engineer studying needing to work on ~~the~~ rebuilding its ~~groundwater~~ piping to water supply? ~~But~~ then a map of the cathedrals aren't so helpful. You might need a different map than — one perhaps providing information about building structures, ground water, piping to its age. It may not need to ~~be~~ show or even name the churches at all.

The map metaphor is helpful, so I want to say one more thing before we move on. It isn't just that maps should be defined differently for different purposes, though that's true. It's also that there is no one map that is ever "true" or the real map. All maps are wrong, now, but not all maps are useless. Some maps are ~~useful~~ useful even when these maps are blatantly "wrong." Like maybe a map of ~~of~~ Africa prior to Europeans began colonizing it. Maybe all the details are now known wrong so it's not useful now for exploration, but perhaps it becomes useful to a historian.

But, even Google maps for SF, arguably a much more accurate map, isn't "true." For one it leave out so much information, even though it's such an efficient ~~map~~ map at displaying info. We don't know everything about SF from this map. And even stuff included is just an abstraction of the real thing.

I stress this b/c I want to say that theoretical models are not the real thing. ~~But it's not so~~ ~~But~~ ~~the~~ ~~fact~~ not b/c they are mathematical — all theories of the world are abstractions, whether the theory is expressed mathematically, ~~or~~ in words, or in diagrams. And so layering on of more info

will ever change that.

Economic models are theoretical ~~of~~ objects that "map" onto the "real world"; but there are many diff. models attempting that. So how do we choose b/w them? How do we decide whether model A or B is correct if all models are fundamentally incorrect?

Economic models therefore ^{must satisfy} ~~have~~ two separate lines of scientific validity. ~~and probably~~ First, the models must be logically or/and mathematically correct. So most of our class focuses on that; we plumb the depths of seemingly simple models to determine what we can say or conclude and the underlying assumptions/conditions/premises for your declarative statements. If a statement or theorem is based on a math error, you clearly know it's "wrong". The conclusion isn't supported by the premises. So a great deal of the mathematical framework is a kind of internal validation to careful studying of models & their associated conclusions like a syllogism. Where we think a ~~model's~~ ^{theory's} conclusion is incorrect, we must first determine if the model guaranteed that at all, and if so, why?

This kind of logical or mathematical verification of a theory is common in the history of science, and particularly in those fields where empiricism ~~was~~ to experimentation seemed to correlate (like economics) or not at all (theoretical physics).

The second line of verification comes from the empirical tradition. ~~and this is~~ Karl Popper in particular is identified with this tradition. Put succinctly, a scientific theory must do more than just try to explain. ~~The~~ Scientific theories must, according to this later tradition, be "falsifiable". A theory is falsifiable iff the theory makes ~~predictions~~ causal predictions. Ideally, these causal predictions would be also observable, but sometimes the causal prediction may be an outcome which are undetectable to the scientist. The theory that a large comet struck Earth several hundred million years ago & destroyed the dinosaurs population, for in Stone, is maybe a difficult theory to test because at first glance, it's not clear how we would falsify that. Stop comets from striking Earth to see if dinosaurs survived anyway? ~~or maybe that~~

Sometimes we find data that ~~correlates~~ correlates with the models predictions, but is this an actual

falsification of the theory? Say that my theory was that ~~the~~ college education caused worker productivity to rise & therefore in equilibrium, caused their wages to rise. That's an empirical & causal prediction:

- if worker A goes to college, she gets W_A^C .
- if worker A DID NOT go to college, she gets W_A^{NC} .

(1) $\rightarrow W_A^C > W_A^{NC}$

- So, just look at worker A both to see, right? Or maybe look at workers in college & workers not in college?

IS: $W_A^{college} \gtrless W_A^{no college}$

(2) $\rightarrow W_A^{college} \stackrel{\text{the same as}}{=} W_B^{no college}$

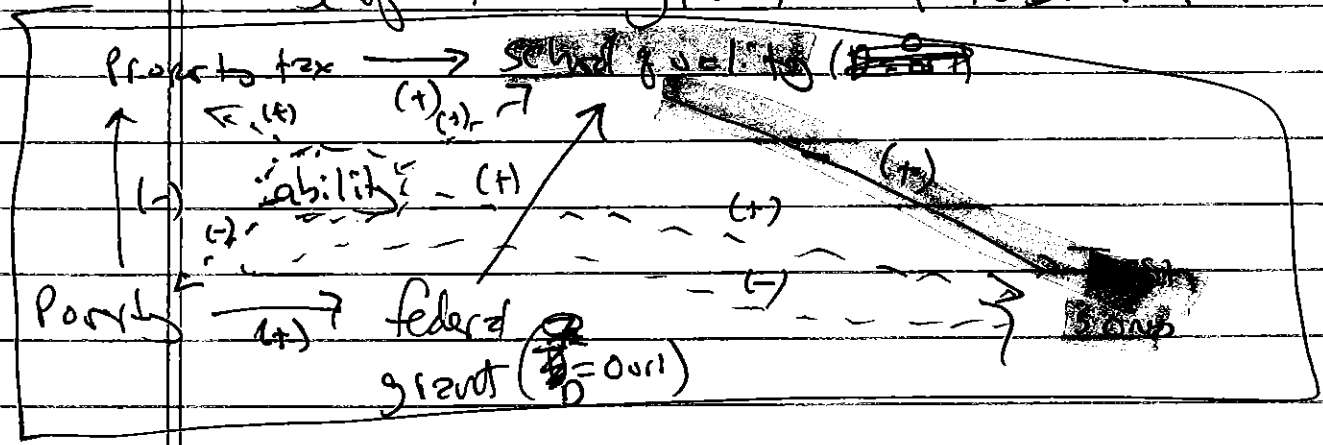
- No, it isn't. This may seem overly technical, but it is critically important, so hear me out. A scientific theory makes ~~quantitative~~ causal predictions, not correlational predictions. That means that falsification ~~is~~ is associated w/ testing equation 1, not 2.

Empirical falsification of a theoretical "causal prediction" maps back to theoretical causal prediction itself. Economic models make very ~~simple~~ causal predictions about simple relationships. Like super simple. Like "Price causes Quantity Demanded to fall" or "wages cause cost to rise". Like simple relationships. It's a very step-by-step approach, is w. very deliberate. But more than that, it is an approach that is simple b/c it recognizes that there are multiple causes of some outcome, but ~~the~~ theoretical causal prediction will be assuming those other causes are fixed, or unchanging, so that we can just focus on one mechanism or a chain of mechanisms at a time. This is the "ceteris paribus" assumption — holding ~~all~~ all things constant.

But, remember in a theoretical, mathematically-based modeling framework, we have this luxury. For example, we will do a lot ^{with a little} of multivariate calculus, & these techniques explicitly "hold constant" other dimensions, or variables, in the model. It's clean, logical, & precise. So when I have a model which says "an increase in schooling will increase wages", that model held constant the causal effect of motivation, IQ, parental education, peer pressure, awesome teachers, ~~things~~ ~~are~~ & so forth on wages.

~~Case~~ But in the real world, when I just ~~take~~ scoop out 1,000 workers ~~from~~ w/ college education \rightarrow 1,000 w/out, none of these things held constant in the data in fact one held constant.

Consider the following scenario. Let's say that poverty causes ~~nutrition to be worse~~, causes schooling to be worse due to property taxes need to pay teacher salaries & school materials. Let's also assume ~~poor~~ federal government grants go to areas with ~~poor~~ worse ^{performing schools.} Finally, let's say that ~~nutrition~~ ~~the~~ ~~grants~~ no grants ~~go to~~ ~~improve~~ have a theory which says that grants will ~~not~~ improve test scores.



* Causal prediction is the pink arrow. It is "increase ^{federal grants} school quality \rightarrow you will increase test scores — holding all determinants of test scores, like ability, ^{to poverty} constant, \rightarrow " (+)

* But notice that if we compare grants places with the grants (D=1) to time without (D=0), we are

not comparing apples to apples, but apples to oranges.
Why?

→ Grants turn on "in the real world"
ble of poverty.

- ↳ Poverty, though, reduces property taxes (-)
- ↳ Property taxes ~~reduce~~ increase school quality (+)
- ↳ Poverty is the consequence of low ability people concentrated in an area which depresses property taxes and lowers school quality AND lowers test scores.

- So our theory predicts if you could just take a lever to turn grants on & off, but hold poverty, etc., the same, THEN you would see a positive correlation b/w grants & scores. But, that thought experiment is based on ~~the~~ what is happening in the model; in the real world, grants are increasing or falling for reasons that aren't "ceteris paribus", & time trends changing ~~may~~ can create ~~spurious~~ spurious correlations.

The challenge for you as young economists is to become competent in both of these forms of validation/verification. ~~And~~ And our class this semester is about the inner logic of formulating theoretical predictions assoc. w/ studying foundational

models about households & firms, & then use them to understand better what econ. teaches us about the world/society, as well as what it does not. This class is about learning to think like an economist, which means learning to build & learn from simple, yet powerful, models. Your econometrics classes w/ Simon West & myself ("Causal Inference") are about the better methods of validation & falsification.

Before I conclude this overview of what a model is scientifically, I wanted to say one last thing about the generality of a model & that is w/ regards to "causal predictions" versus "ethical acceptance/rejection of some aspect of the real world contained in the model".

Let's use a simple example. Let's say we have a theory that some disease (like cholera) is transmitted by water. So, ^{contaminated} drinking water for instance will cause someone to become choleric, & possibly die. That is a causal prediction based on some biological model of the disease. Presumably that's true or false, too, regardless of whether the water supplies are more likely contaminated in ~~over~~ poorer places, & regardless of whether the providers of clean water in an area is a corporation that you love/despise b/c

Q) their ethical/business rect:ces.

Economic models make other, more subtle, distinction b/w scientific ~~rect:ces~~ content and ethical ~~rect:ces~~ judgment. A ~~scientific~~ causal prediction would be "if you increase school quality, you will increase worker wages." Should we, though, do that? That is, just b/c something ^{like a causal} prediction is true, does that mean therefore that ~~we~~ we should do it? ~~not~~

Notice the subtle difference :- language. Scientific theories in their causal predictions are not evaluative judgments - they're simple predictive relationships from an underlying causal model. So in principle, there shouldn't be disagreement b/w two people w/ opposing political views who have the same information about some model's behavioral predictions. But when statements shift from "What is" to "What should some one do", we might expect more disagreement. Just b/c we think the abundance of evidence says min. wage laws will decrease employment & raise unemployment among low skill workers, that does not mean that economists agree about whether that policy should be enacted or not.

This distinction between "what is" & "what should be" is key. You hear it more often called the "positive/normative distinction". Positive theories are ~~some~~ models that make falsifiable claims. Normative theories focus on what we should do. While normative theory does enter into our discussions this semester, most of the time we will be in the world of "positive economic theory".

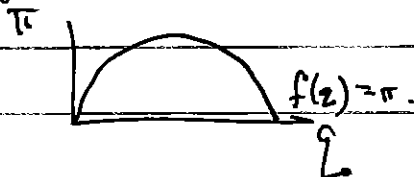
Math Review - I am now going to shift gears a little bit so that I can review some of the basic mathematics we will use this semester. I will now review optimization principles & the calculus ~~to~~ that I need you to learn. Most of this will be focused on techniques to find the optimal value of some function. Forgive me: this is too simple.

I. Maximization of a function of one variable.

ex: Say a manager wishes to maximize profits which are only a function of how much ~~she~~ quantity she sells. Mathematically,

$$1. \quad \pi(q) = f(q)$$

Let's say that there's a rel. b/w π & q like this:



As q ↑, the value of the profit fn. changes, as does the direction of travel.

9. Rules for finding deriv.

1. Let ~~b~~ b is a constant.

$$\frac{db}{dx} = 0.$$

2. Let ~~b~~ ~~multi~~ ~~ply~~ pre-mult. a fn., f.

$$y = bf(x)$$

$$\frac{dy}{dx} = \frac{d(bf(x))}{dx} = b \cdot \frac{df(x)}{dx} = bf'(x)$$

3. $y = x^b$. b is the exponent.

$$\frac{dy}{dx} = \frac{d(x^b)}{dx} = bx^{b-1}$$

ex: x^2

$$\frac{dx^2}{dx} = 2x^{2-1} = 2x$$

4. ~~the~~ natural log of x. $y = \ln x$.

$$\frac{dy}{dx} = \frac{d \ln x}{dx} = \frac{1}{x}$$

5. Let $y = a^x$, where a is constant.

$$\frac{d(\cancel{y})}{dx} = \frac{d(a^x)}{dx} = a^x \ln a$$

5th special case. if $y = e^x$

$$\frac{dy}{dx} = \frac{de^x}{dx} = e^x$$

6. Assume $f(x)$ and $g(x)$ are two fn. & their deriv. exist. (2)

$$\text{Let } y = f(x) + g(x) \quad (\text{Addit. rule})$$

$$\frac{dy}{dx} = \frac{d[f(x) + g(x)]}{dx}$$

$$= \frac{d[f(x)]}{dx} + \frac{d[g(x)]}{dx}$$

$$= f'(x) + g'(x)$$

7. Let $y = f(x) \cdot g(x)$ (Mult. rule)

$$\frac{dy}{dx} = \frac{d[f(x)g(x)]}{dx}$$

$$= f'(x)g(x) + f(x)g'(x)$$

8. Let $y = \frac{f(x)}{g(x)}$

(Quotient rule)

$$\frac{T'B - B'T}{B^2}$$

$$\frac{dy}{dx} = \frac{T'B - B'T}{B^2}$$

if $g(x) \neq 0$

$$\left. \begin{array}{l} T' = f'(x) \\ B' = g'(x) \\ B^2 = g(x)^2 \end{array} \right\} \rightarrow \frac{dy}{dx} = \frac{f'(x)g(x) - g'(x)f(x)}{g(x)^2}$$

9. Let $y = f(x)$ and f' & g' exist.
 $x = g(z)$

$$\frac{dy}{dz} = \frac{d}{dz} (f(g(z)))$$

$$= \frac{dy}{dx} \cdot \frac{dx}{dz}$$

$$= \frac{df}{dx} \cdot \frac{dg}{dz}$$

$$\frac{dy}{dz} = f'g' \quad (\text{Chain rule})$$

~~max/min~~ Multiple Choice

ex: Find ~~max~~ optima of $y = 3x^2 + 12x + 1$
 Check if it is max or min using FOC & SOC.

$$\text{FOC} = \frac{dy}{dx} = 6x + 12 = 0$$

$$\frac{6x}{6} = \frac{-12}{6}$$

$$x = -2$$

$$\text{SOC} = \frac{d^2y}{dx^2} = 6 > 0$$

If $\text{SOC} > 0$, it's a min.

If $\text{SOC} < 0$, it's a max.

Show on graph using graph.

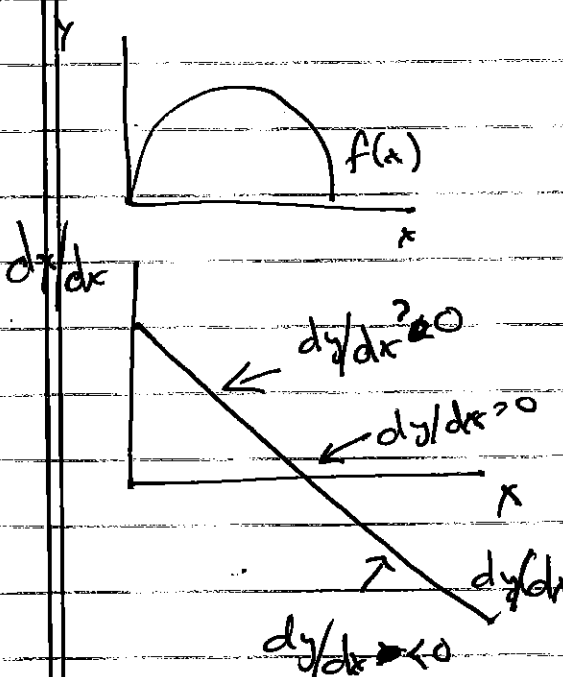
Maximization w/ one vbl.

let $y = f(x)$

$\frac{dy}{dx}$ ~ derivative of y wrt x . measures the rate of change in the y vbl as x changes.

↳ ALSO $f'(x)$

by some infinitesimal amount.
Measures the slope of the y fn. at some point on the fn.
~~more~~ equally x .



← Notice that the slope's value is decreasing as x increases.

$\left(\frac{d}{dx}\right)\left(\frac{dy}{dx}\right)$: second derivative
 $= f''(x)$

$\frac{d^2y}{dx^2} < 0$

ex: $y = 3x^2 + 12x + 1$

$\frac{dy}{dx} = 6x + 12$

set $dy/dx = 0$. Solve for x .

$\frac{d^2y}{dx^2} = 6$

$\frac{dy}{dx} = 0, \quad 6x + 12 = 0$
 $\frac{6x}{6} = \frac{-12}{6}$

$x = -2$

$\frac{d^2y}{dx^2} = \frac{d}{dx}(6x + 12)$
 $= 6$

-2 is the option? I sit max or min?

max or min →

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ex: Let \hat{q} (d1-f:t) equal:

$$\hat{q} = 1000q - 5q^2$$

For $\frac{d\pi}{dq} = 1000 - 10q = 0$

$$\frac{10q}{10} = \frac{1000}{10}$$

$q^* = 100$

So $\frac{d^2\pi}{dq^2} = -10 < 0$ (max)

↑
 global
 max b/c
 second deriv
 is always -10.

Therefore $q^* = 100$ is global max.

Opt. of Mult. Var. fn.

Partial deriv.
(S)

Suppose health is some fn. of carbs (C), protein (P), & fats (F):

$$y = f(C, P, F)$$

We wonder what happens to her health if she increases her cons. of carbs, but holding constant P & F.

~~So~~ $\frac{\partial y}{\partial C} = \frac{\partial f}{\partial C} = f_C(C, P, F)$ or $f_1(C, P, F)$

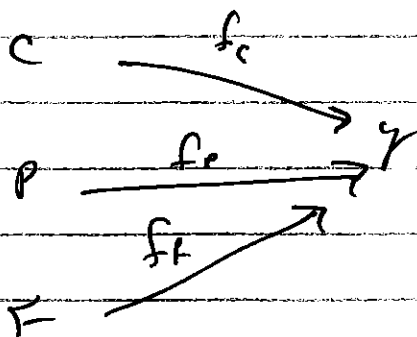
Calculating partials (Schock)

ex 1: let $y = f(x_1, x_2) = ax_1^2 + bx_1x_2 + cx_2^2$

$$\frac{dy}{dx_1} = 2ax_1 + bx_2$$

$$\frac{dy}{dx_2} = bx_1 + 2cx_2$$

Partials are math. expression of ceteris paribus.

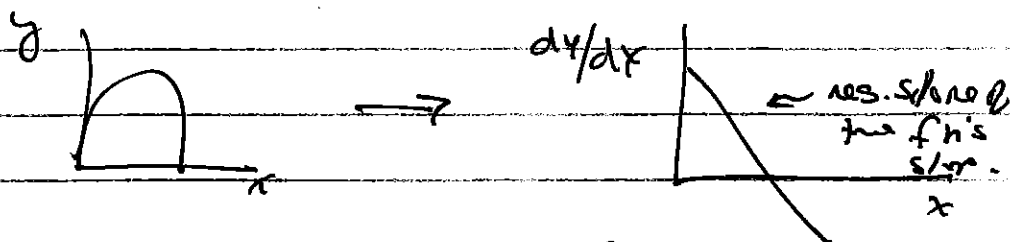


- Each causes y .
 - Partial focuses only on one arrow.
- $\frac{dy}{dc} = \frac{df}{dc}$ would be top arrow

Second order partial derivatives

What about the partial of a partial deriv?

Recall when we did this with a ~~one~~ second deriv in one variable case. ~~That~~, Yea it was easy:



it ~~was~~ is slightly more complex w/ 2 or more vars

$$1. \quad y = (x_1, x_2) = ax_1^2 + bx_1x_2 + cx_2^2$$

first partials

$$f_1 = \frac{dy}{dx_1} = 2ax_1 + bx_2$$

$$f_2 = \frac{dy}{dx_2} = 2cx_2 + bx_1$$

second partials

Note that there are four second partials, not 2:

$$f_{11} = 2a$$

$\begin{matrix} \text{P} \\ \text{P} \end{matrix}$

$$f_{12} = b$$

$$f_{21} = b$$

$$f_{22} = 2c$$

→ Notice: $f_{12} = f_{21}$
coincidence? No.
see below.

Young's theorem - The order in which partial diff. is conducted to evaluate second-order partials doesn't matter!

$$f_{ij} = f_{ji} \quad \text{for any pair of vbls } x_i \text{ \& } x_j.$$

Young's theorem also implies that the matrix of all second-order partials of a fn. is symmetric.

$$\begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix} = \begin{bmatrix} 2a & b \\ b & 2c \end{bmatrix}$$

the upper right is a hermitian image of the lower left.

Total differential:

Say that all the x 's in $f(x, y)$, were allowed to change by a small amount. Then the ~~the~~ TOTAL CHANGE in y ("total differential") is just the linear combination, or sum, of each partial derivative multiplied by the change in that variable, x .

Let $y = f(x_1, x_2, \dots, x_n)$ for n variables.

$$dy = \frac{df}{dx_1} dx_1 + \frac{df}{dx_2} dx_2 + \dots + \frac{df}{dx_n} dx_n$$

$$dy = f_1 dx_1 + f_2 dx_2 + \dots + f_n dx_n$$

Direct vs. indirect effects.

~~total~~

Let $y = f(x_1(a), x_2(a), x_3(a))$

$$\frac{dy}{da} = \frac{df}{dx_1} \frac{dx_1}{da} + \frac{df}{dx_2} \frac{dx_2}{da} + \frac{df}{da}$$

$$= \underbrace{f_1 \frac{dx_1}{da} + f_2 \frac{dx_2}{da}}_{\text{indirect effect of } a \text{ on } y} + \underbrace{f_a}_{\text{direct effect}}$$

indirect effect of a on y direct effect.

Implicit Fn.

- if the value of a fn. is held constant, then the independent vbls can no longer take on any values. Rather they can take on only those set of values that result in the fn. retaining the req. value.
- called "implicit" b/c when you set the fn. equal to some value, an "implicit" is created among the independent variables entering into the fn.

ex: $x + 2y = 4$

$$\frac{2y}{2} = \frac{4-x}{2}$$

$$y = 2 - \frac{1}{2}x$$

↓

let $y = 0$.

$$y = 2 - \frac{1}{2}x = 0$$

$$2 - \frac{1}{2}x = 0$$

$$\frac{1}{2}x = 2$$

$$x = 4$$

if $y = 0$, x must equal 4.

NOTE: diff. x values yield diff. values of y . B/c we did not set y to any particular value. But, had we set y to a particular value, we are setting x to be only one value.

another ex., this time w/ multiplex's,

$$\text{let } y = f(x_1, x_2)$$

Take total diff of y .

$$dy = \frac{\partial f}{\partial x_1} dx_1 + \frac{\partial f}{\partial x_2} dx_2$$

Now set y to 0. dy , therefore, is 0.

$$dy = 0$$

$$\frac{\partial f}{\partial x_1} dx_1 + \frac{\partial f}{\partial x_2} dx_2 = 0$$

$$f_1 dx_1 + f_2 dx_2 = 0$$

$$f_1 dx_1 = -f_2 dx_2$$

$$-\frac{f_1}{f_2} = \frac{dx_2}{dx_1}$$

if $dy=0$, then we necessarily are requiring x_1 to x_2 to have a particular rate of exchange. ~~the~~ we are requiring a "trade-off" equation, here, the ratio of f_1 to f_2 times -1.

Suppose that an agent wishes to max
a multivariate fn, $y = f(x_1, \dots, x_n)$.

Q1: What would be
total change in y
if firm achieves x_1 ?

$$\frac{dy}{dx_1} = \frac{df(x_1, \dots, x_n)}{dx_1}$$

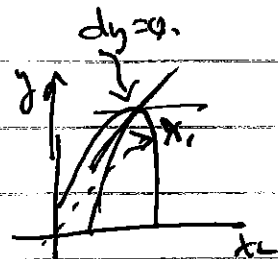
$$dy = f \cdot dx_1$$

it'd
be the
rate of
ch.

X how much

Q2: What are FOC & SOC for max when multivariate?

Necessary conditions are $dy = 0$.



But note, there are 2 ways to induce change in y :
- thru x_1 & thru x_2 .
- therefore, we are necessarily requiring
that the partials in both directions
be set to zero.

FOC: Necessary condition for a max of fn $f(x_1, \dots, x_n)$ is that $dy=0$ for any combo. of small ch. in x 's

$$f_1 = f_2 = \dots = f_n = 0$$

SOC: $f_{ii} < 0$.

Second partial derivatives must be negative to ensure the max.

ex: $y = -(x_1 - 1)^2 - (x_2 - 2)^2 + 10$

$$y = -(x_1 - 1)(x_1 - 1) - (x_2 - 2)(x_2 - 2) + 10$$

$$y = -(x_1^2 - 2x_1 + 1) - (x_2^2 - 4x_2 + 4) + 10$$

$$y = -x_1^2 + 2x_1 + 1 - x_2^2 + 4x_2 - 4 + 10$$

$$y = -x_1^2 + 5 + 2x_1 - x_2^2 + 4x_2$$

$$y = -x_1^2 + 2x_1 + 4x_2 - x_2^2 + 5$$

~~FOC~~: max y choosing optimal x_1^* & x_2^* .

FOC 1: $\frac{dy}{dx_1} = -2x_1 + 2 = 0$

$$\frac{2x_1}{2} = \frac{2}{2}$$

$$x_1^* = 1$$

$$\text{FOC 2: } \frac{dy}{dx_2} = 4 - 2x_2 = 0$$

$$\frac{4}{2} = \frac{2x_2}{2}$$

$$x_2^* = 2$$

$$x_1^* = 1; x_2^* = 2 \quad \text{to optimize } y.$$

$$f_{11} = \frac{d^2y}{dx_1^2} = -2 < 0$$

}
MAX

$$f_{22} = \frac{d^2y}{dx_2^2} = -2 < 0$$

The envelope theorem implicit fcn. th.
An app. of the ~~env.~~ theorem.

- how the optimal value for z in changes when a parameter of the f_i - changes.

ex: let $y = -x^2 + ax$

we can calculate x^* .

$$\frac{dy}{dx} = -2x + a = 0$$

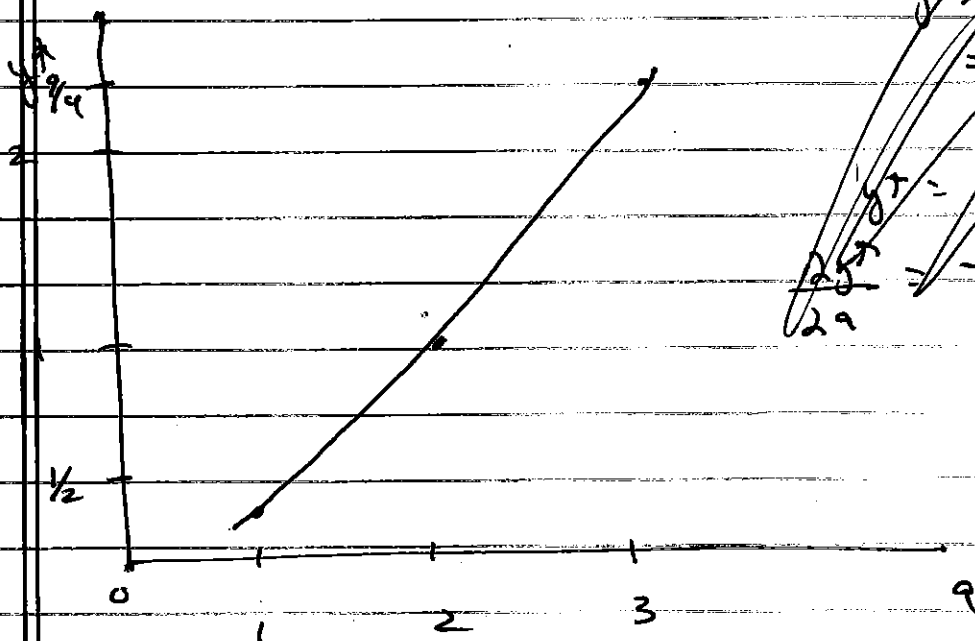
$$\frac{a}{2} = \frac{2x}{2}$$

$$x^* = \frac{1}{2} a$$

Now, notice that x^* is a fn. of a . So, notice:

a	x^*	y^*
0	0	0
1	$\frac{1}{2}$	$\frac{1}{4}$
2	1	1
3	1.5	$\frac{9}{4}$

$$\begin{aligned} x^* &= \frac{1}{2}a \\ y &= -x^2 + ax \end{aligned}$$



$$\begin{aligned} y^* &= -\left(\frac{1}{2}a\right)^2 + a\left(\frac{1}{2}a\right) \\ &= -\frac{1}{4}a^2 + \frac{1}{2}a^2 \\ &= \frac{1}{4}a^2 \end{aligned}$$

The envelope theorem states that the slope of the rel. b/w y^* and a can be found by calculating the slope of the auxiliary rel. ~~be~~ found by substit. the respective optimal values for x into the obj fn. to calculate $\frac{dy^*}{da}$

$$\begin{aligned} y^* &= -\left(\frac{1}{2}a\right)^2 + a\left(\frac{1}{2}a\right) \\ &= -\frac{1}{4}a^2 + \frac{1}{2}a^2 \end{aligned}$$

$$y^* = \frac{1}{4}a^2$$

$$\frac{dy^*}{da} = -\frac{1}{2}a = x^*$$

If we are interested in how y^* changes as a changes, then calculate the slope of y directly holding X constant at its optimal value, then calculate $\frac{dy}{da}$



env. th.

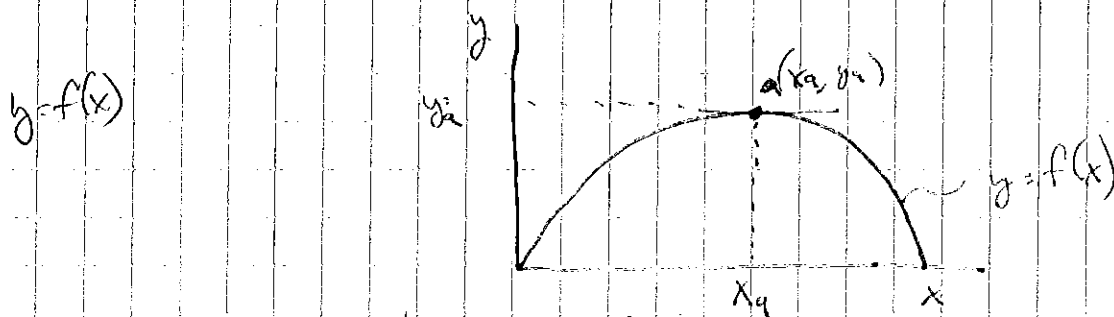
Lecture 1 outline

(1)

1. What are ^{econ} models? (Silberburg, NS) Distinctions
- truth, usefulness, what is a "good theory"? testability, math, Popper, assumptions
- Positive & Normative
- What tools will we use?
 - * ~~Differential~~ Calculus: mostly derivatives, & integration.
 - * Game Theory
 - * "optimization"
2. What should you learn outside of my lectures.
 - (a) NS chapter 2
 - (b) For intuition, any intermediate text, like Varian or Nicholson.
3. I will miss several days, so we will have to make them up. I will need to get schedules. The sooner the better.

Maximization example

- Finding the max value for a function w/ several variables requires
- Simple case: one variable.

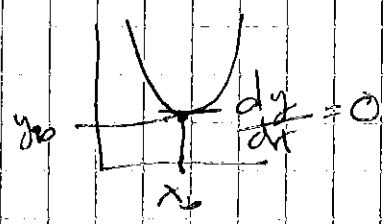


- Visually, point (x_0, y_0) is the maximum of the function, $f(x)$. y_0 is the highest value real number in the set of real values contained in $f(x)$.
- ~~point~~ ~~slope~~ The maximum can also be understood in terms of ~~the~~ the function's slope. The slope is the rate of change in y when x increases by a small amount. When that rate of change is zero, y is no longer rising. A necessary condition for (x_0, y_0) to be the max by the measure of slope is that the slope be 0.

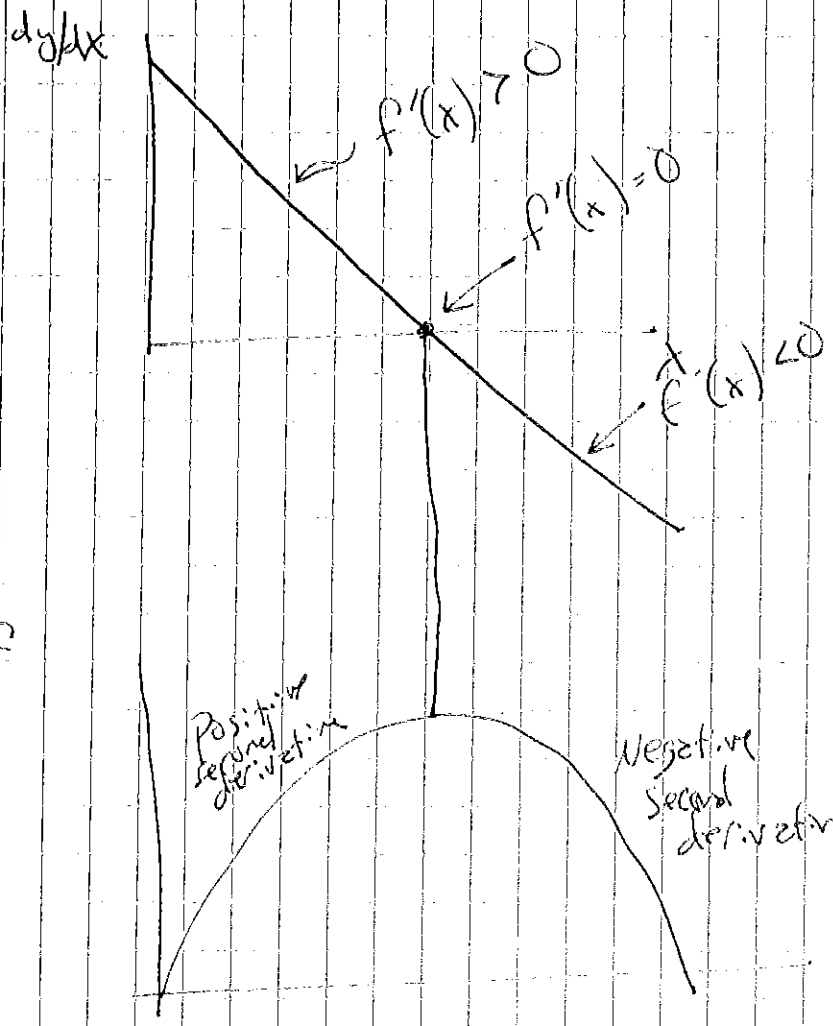
That is, $\frac{dy}{dx} = f'(x) = 0$

$\frac{\Delta y}{\Delta x}$
run

where the "d" is the derivative of y wrt a change in x. But it is only necessary condition; it isn't sufficient, b/c this also has a slope of 0:



~~what we do~~
we can, though, take the derivative function, $f'(x)$, and plot its values.



To determine whether the point you found is a maximum of the function, you need to take the derivative of the slope formula. If it is negative at your solution, then it is a max.

$$\frac{d^2y}{dx^2} < 0$$

Rules for Finding derivatives

6

1. If b is a constant, then:

$$\frac{db}{dx} = 0$$

2. If b is a constant, then

$$\frac{d[b f(x)]}{dx} = b f'(x)$$

3. If b is a constant, then

$$\frac{dx^b}{dx} = b x^{b-1}$$

4. $\frac{d \ln x}{dx} = \frac{1}{x}$

5. $\frac{da^x}{dx} = a^x \ln a$ for any constant a .

6. Assume $f(x)$ & $g(x)$ are two functions to which the deriv. exist. Then

$$\frac{d[f(x) + g(x)]}{dx} = f'(x) + g'(x)$$

7. $\frac{d[f(x) \cdot g(x)]}{dx} = f'(x)g(x) + g'(x)f(x)$

8. $\frac{d[f(x)/g(x)]}{dx} = \frac{f'(x)g(x) - f(x)g'(x)}{[g(x)]^2}$

Quotient Rule:

$$\frac{f'B - B'T}{B^2}$$

9. Let $y = f(x)$, & $x = g(z)$, & both deriv. exist. Then:

$$\frac{dy}{dz} = \frac{d[f(g(z))]}{dz} = \frac{df}{dx} \cdot \frac{dx}{dz} = \frac{df}{dx} \frac{dg}{dz}$$

Chain Rule

Over

Multiple variables

Suppose a person wants to achieve ^{maximum} some level of health by consuming combinations of protein, carbs + fats. Let y be the measure of health,

$$y = f(C, P, F)$$

The partial derivative is used here as we want to know what happens to health when only one changes.

$$\frac{dy}{dC} = f_C(C, P, F)$$

the change itself would be:

$$dy = \frac{df}{dC} dC$$

The change in your overall health would be ~~the~~ ~~change~~ equal to the change in your cons. of carb. multiplied by the slope measured in the C direction.

example:

1. If $y = f(x_1, x_2) = ax_1^2 + bx_1x_2 + cx_2^2$

$$\frac{df}{dx_1} = f_1 = 2ax_1 + bx_2$$

(holding x_2 constant)

and $\frac{df}{dx_2} = f_2 = bx_1 + 2cx_2$

(holding x_1 constant)

2. $y = f(x_1, x_2) = e^{ax_1 + bx_2}$

$$\frac{dy}{dx_1} = f_1 = a \cdot e^{ax_1 + bx_2}$$

3. $y = f(x_1, x_2) = a \ln x_1 + b \ln x_2$

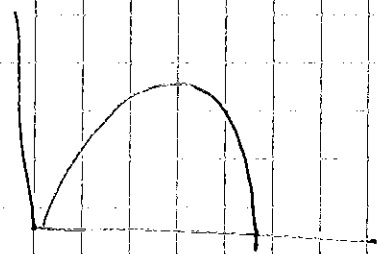
$$\frac{\partial f}{\partial x_1} = f_1 = \frac{a}{x_1}$$

$$\frac{\partial f}{\partial x_2} = \frac{b}{x_2}$$

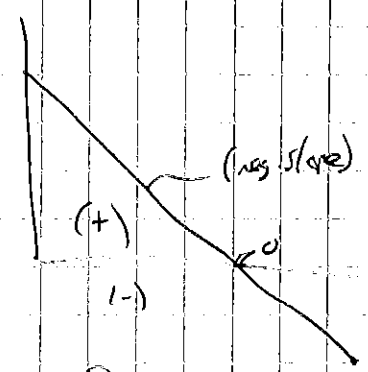
~~Yours' Theorem~~

Second Order Partial Deriv.

~~Calc~~ - Thinking back to univariate case, we are calculating the slope of the slope function.



→



Multivariate:

$$\frac{\partial(\frac{\partial f}{\partial x_i})}{\partial x_j} = \frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i} = f_{ij}$$

1. $y = f(x_1, x_2) = ax_1^2 + bx_1x_2 + cx_2^3$

$$f_1 = 2ax_1 + bx_2$$
$$f_2 = 2cx_2 + bx_1$$

$$f_{11} = \frac{\partial^2 f}{\partial x_1^2} = f_{11} = 2a$$

$$f_{12} = \frac{\partial^2 f}{\partial x_1 \partial x_2} = f_{21} = b$$

$$f_{21} = \frac{\partial^2 f}{\partial x_2 \partial x_1} = f_{12} = b$$

$$f_{22} = \frac{\partial^2 f}{\partial x_2^2} = 2c$$

~~the red~~

You can do the red. Notice:
 $f_{12} = f_{21} = b.$

Young's Theorem

- The order in which partial differentiation is conducted to evaluate second-order partial derivatives does not matter:

$f_{ij} = f_{ji}$

for any pair of variables, x_i & x_j .

- It will also imply that the matrix of all second-order partial derivatives of a function is symmetric.

Total Differential

Let $y = f(x_1, \dots, x_n)$. If all the x_i 's are allowed to vary by a small amount, then the total effect will be the sum of the changes.

$dy = f_1 \frac{df}{dx_1} dx_1 + \frac{df}{dx_2} dx_2 + \dots + \frac{df}{dx_n} dx_n$

$[dy = f_1 dx_1 + f_2 dx_2 + \dots + f_n dx_n]$

analogous to ~~the univariate~~ story

(more general form of wealth functions earlier.)

FOC: $f_1 = f_2 = \dots = f_n = 0$.

This is called the critical point. But could be a min or max. All hilltops are flat, but not all flat places are hilltops.

We will need to look at second partials.

~~Implication~~

"For a specific point to provide a (local) maximum value to the function it must be the case that no small movement in any direction can increase its value."



Implicit Function

We can rewrite a dependent var. like this:

$$y = mx + b$$

$$y - mx - b = 0$$

$$f(x, y, m, b) = 0$$

Functions written like this are called implicit fns. b/c the rel. b/w the variables & parameters are implicitly present in the equation rather than calculated.

ex: $x + 2y - 4 = 0$
 $x = 4 - 2y = -2y + 4$
 or
 $y = \frac{4 - x}{2} = 2 - \frac{x}{2}$
 $\frac{-2y}{-2} = \frac{x - 4}{-2}$
 $y = 2 - \frac{x}{2}$

Derivatives:

Say $f(x, y) = 0$ w/ TP of $f_x dx + f_y dy = 0$

then, $f_y dy = -f_x dx$

$$\left[\frac{-dy}{dx} = \frac{f_x}{f_y} \right]$$

envelope theorem

$$a=1 \quad y = x - x^2$$

$$y = x(1-x)$$

$$\frac{dy}{dx} = 1 - 2x = 0$$

$$\frac{1-2x}{2} = \frac{x^* - 1/2}{2} = x^* = 1/2$$

$$\text{so } y^* = \frac{1}{2}(1 - \frac{1}{2}) = \frac{1}{4}$$

An app. of implicit fn theorem. First an ex:

$$y = -x^2 + ax$$

The envelope theorem deals w/ solution values for y to x when the parameters themselves change.

It is studying how the optimal value of a function changes when the parameter changes. The shortcut is:

$$\frac{dy}{da} = x$$

at x^* , we have:

$$\frac{dy^*}{da} = x^* = 1/2$$

$$a=2:$$

$$y = -x^2 + 2x$$

$$\frac{dy}{dx} = -2x + 2 = 0$$

$$x = 1$$

~~$$\frac{dy^*}{da} = \frac{dy}{da} \left\{ x = x^*(a) \right\}$$~~

Multivariate

Finding optimal value for y consists of solving n FOC eq. of the form:

$$\frac{dy}{dx_i} = 0 \quad (i=1, \dots, n)$$

to yield $(x_1^*, x_2^*, \dots, x_n^*)$ that depend implicitly on a. Subst. all x_i 's into obj. fn. to get y^* .

$$y^* = f(x_1^*, x_2^*, \dots, x_n^*)$$

$$= f(x_1^*(a), x_2^*(a), \dots, x_n^*(a), a)$$

FOC w/ta

$$\frac{dy^*}{da} = \frac{df}{dx_1^*} \frac{dx_1^*}{da} + \frac{df}{dx_2^*} \frac{dx_2^*}{da} + \dots + \frac{df}{dx_n^*} \frac{dx_n^*}{da}$$

But, b/c of FOC (ie, $\frac{\partial f}{\partial x_i} = 0 \forall i$) all the terms are 0 at their optimal values, giving us the envelope result:

$$\frac{dy^*}{da} = \frac{\partial f}{\partial a}$$

where the derivative is evaluated at optimal values for x .

Constrained Max

Let an agent have obj. fn:

$$y = f(x_1, x_2, \dots, x_n)$$

~~is~~ facing constraint that only certain values of x be used.

$$g(x_1, \dots, x_n) = 0$$

Choose values of x_1, \dots, x_n that maximizes y .

Lagrangian method

$$L = f(x_1, \dots, x_n) + \lambda g(x_1, \dots, x_n)$$

↳ the Lagrangian multiplier.
Notice that when the constraint holds L and f are equal b/c $g(x_1, \dots, x_n) = 0$.

$$FOC = \frac{\partial L}{\partial x_1} = f_1 + \lambda g_1 = 0$$

$$\frac{\partial L}{\partial x_2} = f_2 + \lambda g_2 = 0$$

$$\vdots$$

$$\frac{\partial L}{\partial x_n} = f_n + \lambda g_n = 0$$

$$\frac{\partial L}{\partial \lambda} = g(x_1, \dots, x_n) = 0$$

~~Math for a~~

Maximization

These FOC equations are the conditions for a critical point for the \mathcal{L} function. Notice there are $n+1$ equations (one for each x and λ) & $n+1$ unknown variables (x & λ). The equations allow us to solve for x, \dots, λ . Solution will have two properties:

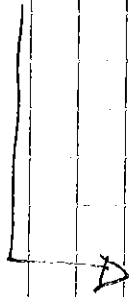
- ① x 's will obey constraints b/c the last equation ~~also~~ imposes that condition.
- ② among the x 's values satisfying the constraint, those that also solve the equations will make \mathcal{L} as large as possible.

Interpretation

λ

Rewrite the FOC equations:

$$\frac{f_1}{-g_1} = \frac{f_2}{-g_2} = \dots = \frac{f_n}{-g_n} = \lambda$$



λ is equal to the ratio of f_i to g_i .
 At the critical point, the ratio of f_i to g_i is the same for every x_i .
 Numerator: Marginal contributor of each x_i to the function f .
 Denominator: "Marginal benefit" of an increase with x_i to f .

The denominator will make more sense when we see it in ~~an~~ actual economic application. But in our application, it will usually be a marginal cost.

ex: assume the constraint ~~is~~ requires that total spending on x_1 and x_2 to be given by a fixed dollar amount, F . Hence:

$$p_1 x_1 + p_2 x_2 = F$$

where p_i is the market price of good x_i . The constraint would be rewritten as:

$$g(x_1, x_2) = F - p_1 x_1 - p_2 x_2 = 0$$

Therefore, $\frac{dg}{dx_1} = -p_1$

And so,

$$\frac{f_1}{g_1} = \lambda = \frac{f_1}{p_1} = \lambda$$

Here we see that the derivative, g_1 , reflects the per unit cost of an additional unit of x_1 .

Lagrange multiplier is, now, a MB/MC ratio

$$\lambda = \frac{MB \text{ of } x_i}{MC \text{ of } x_i}$$

Duality

Key insights in both the theory of the consumer & the theory of the firm are borne from seeing the rel. b/w obj. fn. & constraints can be reversed w/out changing the solution — called duality theory. As we will depend heavily on it, we should try to understand it abstractly first.

Any ~~conv~~ constrained maximization problem has an associated dual problem in constrained minimization.

An example we will encounter:

- the consumer will maximize utility subject to his BC.

- it can be reformulated as an expenditure min. subject to a "utility" constraint where utility is held at the value solved in the primal problem.

Other apps: a firm will max output subject to a cost constraint, or it will min. cost subject to an output constraint. Two perspectives on the same decision, but through duality theory so to speak we will learn more about behavior embedded in our models.

ex: let $y = -x_1^2 + 2x_1 - x_2^2 + 4x_2 + 5$

$x_1 + x_2 = 1$

for $\mathcal{L} = -x_1^2 + 2x_1 - x_2^2 + 4x_2 + 5 + \lambda(1 - x_1 - x_2)$

$\frac{\partial \mathcal{L}}{\partial x_1} = -2x_1 + 2 - \lambda = 0$

$\frac{\partial \mathcal{L}}{\partial x_2} = -2x_2 + 4 - \lambda = 0$

$\frac{\partial \mathcal{L}}{\partial \lambda} = 1 - x_1 - x_2 = 0$

Solve for x_1^*, x_2^*, λ^*

$-2x_1 + 2 = -2x_2 + 4$

$x_1 - 1 = x_2 - 2$

$x_1 = x_2 = 1$

$1 - x_1 - x_2 = 0$

$1 - [x_2^* - 1] - x_2^* = 0$

$\frac{d}{dx_2} = \frac{2x_2^*}{2} = 1$

$x_2^* = 1$

$\lambda^* = 2$

$\lambda^* = 2$

$1 - x_1^* - x_2^* = 0$

$x_1^* = 0$

if $x_1 = 0, x_2 = 1$, then $y =$

$y = -(0)^2 + 2(0) - (1)^2 + 4(1) + 5 = 8$

~~max $x_1 + x_2$ st. $y = -x_1 + 2x_2$ $x_1^2 + x_2^2 = 5$~~

Envelope Th. in constrained Max.

Suppose we seek max value of:

$$y = f(x_1, \dots, x_n; a)$$

$$\text{st. } g(x_1, \dots, x_n) = 0$$

$$L = f(x_1, \dots, x_n; a) + \lambda g(x_1, \dots, x_n)$$

and solve for FOC for optimal, constrained, values of x_i^* .

Envelope th.: Also, when we solve for x_i^* & put back in to L^* , we get y^*

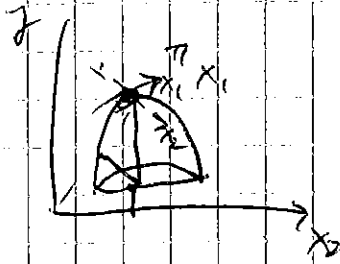
Now, say we want to know how the optimal value of y^* changes if we vary the parameter. (ex, how will a consumer's utility [solid number] change if we vary the price of good x ?)

$$\left[\frac{dy^*}{da} = \frac{dy}{da} (x_1^*, \dots, x_n^*) \right]$$

This is the env. theorem applied.

2 vlds

~~⊗~~



$$f_{11} < 0$$

$$f_{22} < 0$$

are two intuitive counterparts. But what about:

~~f_{12} or f_{21} ?~~
 cross-partials

formal analysis

~~$dy = f_1 dx_1 + f_2 dx_2$~~

① T.O.

② I.O.

let $y = f(x_1, x_2)$
 $dy = f_1 dx_1 + f_2 dx_2$

$$d^2y = f_{11} dx_1^2 + f_{22} dx_2^2 + f_{12} dx_1 dx_2 + f_{21} dx_2 dx_1$$

Jour's m:

$$d^2y = f_{11} dx_1^2 + 2f_{12} dx_1 dx_2 + f_{22} dx_2^2$$

we need $d^2y < 0$ for so. \therefore sum of R/Hs must be neg. what condition?

⊗ (i) let $dx_2 = 0$
 $f_{11} dx_1^2$
 \rightarrow (i)

and by symmetry:

- ①
- ②
- ③

$$f_{11} < 0$$

$$f_{22} < 0$$

interior terms: $2f_{12} dx_1 dx_2$. what?

Concavity in unconstrained max

$$H \equiv \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}$$

1. Neg/pos. Def. we say the matrix is neg/pos. definite or semi-definite.

pos def : if all leading pm are pos.
neg def : " " " " and alternating in sign starting w/ minus.

So, back to unconstrained max. we need to know if our function is at a max. This is in matrix algebra equiv to whether the det. of H is neg. def.

$$H = \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}$$

1st princ. location minor 1: $f_{11} < 0$ by assumption.
2nd " " " " : $f_{11}f_{22} - f_{12}f_{21}$
 $\left[\begin{matrix} f_{11}f_{22} - f_{12}f_{21} > 0 \\ f_{12} = f_{21} \end{matrix} \right]$

this condition is, w/ $f_{11} < 0$ & $f_{22} < 0$, enough to ensure that $d^2y < 0$ at the critical points, x_1^* & x_2^*

SOC:

Let $y = f(x)$

$\frac{dy}{dx} = f'(x) = 0$ ← necessary.

$dy = f'(x) dx$

To det if it is a max or not a min, then

$\frac{d(dy)}{dx} = \frac{d[f'(x)]}{dx} = f''(x) dx$

$\frac{d^2y}{dx^2} = f''(x) dx$

$d^2y = f''(x) dx^2$

* $[d^2y < 0]$ implies that $f''(x) dx^2 < 0$, and $dx^2 > 0$, so SOC is $f''(x) < 0$.
↳ required.

So

2 UBS:

$y = f(x_1, x_2)$

$\frac{\partial y}{\partial x_1} = f_1 = 0$

$\frac{\partial y}{\partial x_2} = f_2 = 0$

(1) Total diff. y with all arguments
 $dy = f_1 dx_1 + f_2 dx_2$

(2) 2nd differential of

$d^2y = f_{11} dx_1^2 + f_{12} dx_1 dx_2 + f_{21} dx_1 dx_2 + f_{22} dx_2^2$

(3) Young's Eq. $f_{12} = f_{21}$

(4) $d^2y = f_{11} dx_1^2 + 2 f_{12} dx_1 dx_2 + f_{22} dx_2^2$

MUST be negative. (i.e. $d^2z < 0$). Therefore, what conditions yield that?

$$f_{11} < 0$$
$$f_{22} < 0$$

f_{12} ? the cross-partial effects.

$$|D| = \begin{vmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{vmatrix} = f_{11}f_{22} - f_{12}^2 > 0$$

the neg. condition is: $f_{11}f_{22} - f_{12}^2 > 0$

Constrained Max:

$$\max_{(x_1, x_2)} y = f(x_1, x_2) \quad \text{st.} \quad b_1 x_1 + b_2 x_2 = C.$$

$$J = f(x_1, x_2) + \lambda (C - b_1 x_1 - b_2 x_2)$$

$$\frac{\partial J}{\partial x_1} = f_1 - \lambda b_1 = 0$$

$$\frac{\partial J}{\partial x_2} = f_2 - \lambda b_2 = 0$$

$$\frac{\partial J}{\partial \lambda} = C - b_1 x_1 - b_2 x_2 = 0$$

then we solve the system to find x_1^* , x_2^* & λ^* .
- 3 unknowns in 3 equations.

SEC: Now we need to know if at those solutions, any movements away will cause values to fall, using 2nd order total diff.

$$dy = f_1 dx_1 + f_2 dx_2$$

$$d^2y = f_{11} dx_1^2 + 2f_{12} dx_1 dx_2 + f_{22} dx_2^2$$

BUT, w/ constraint $b_1 x_1 + b_2 x_2 = C$, there are explicit constraints which x_1/x_2 can take on, b/c the constraint forces tradeoffs to be made if you were to increase one. For instance, at the point where the constraint is binding, $x_1 \uparrow$ will only occur if x_2 falls by:

$$\begin{aligned} b_1 x_1 + b_2 x_2 &= C \\ b_1 x_1 &= C - b_2 x_2 \\ \frac{b_1}{b_1} x_1 &= \frac{C - b_2 x_2}{b_1} \end{aligned}$$

$$x_1 = \frac{C}{b_1} - \frac{b_2}{b_1} x_2$$

So, dx_1 cannot be anything.

Tricks

- Two substitutions will make.

Therefore, we must substitute constraints into d^2y . But x_1 & x_2 aren't in there, only dx_1 & dx_2 are. Therefore,

Second subst from the 1st

$$\frac{dx_1}{dx_2} = -\frac{b_2}{b_1}$$

$$dx_1 = \frac{-b_2 dx_2}{b_1}$$

$$dx_2 = \frac{-b_1 dx_1}{b_2}$$

AND

for:

$$f_1 - \lambda b_1 = 0$$

$$f_2 - \lambda b_2 = 0$$

$$\lambda = \frac{f_1}{b_1} = \frac{f_2}{b_2}$$

$$\frac{f_1}{f_2} = \frac{b_1}{b_2}$$

Now, substitute the constraint into our SDC to get.

$$d^2y = f_{11} dx_1^2 + 2f_{12} dx_1 dx_2 + f_{22} dx_2^2$$

$$= f_{11} dx_1^2 + 2f_{12} dx_1 \left[\frac{-b_1}{b_2} dx_1 \right] + f_{22} \left[\frac{-b_1}{b_2} dx_1 \right]^2$$

$$= f_{11} dx_1^2 - \frac{2b_1}{b_2} f_{12} dx_1^2 + f_{22} \frac{b_1^2}{b_2^2} dx_1^2$$

subst. for

~~$$= \frac{f_{11} dx_1^2}{b_2^2} \left(f_{11} b_2^2 - 2b_1 f_{12} b_2 + f_{22} \frac{b_1^2}{b_2^2} \right)$$~~

~~$$= \frac{dx_1^2}{b_2^2} \left(f_{11} b_2^2 - 2b_1 f_{12} b_2 + f_{22} \frac{b_1^2}{b_2^2} \right)$$~~

$$= f_{11} dx_1^2 - \frac{2f_1}{f_2} f_{12} dx_1^2 + f_{22} \left(\frac{f_1}{f_2} \right)^2 dx_1^2$$

$$= \frac{dx_1^2}{f_2^2} \left(f_{11} f_2^2 - 2f_1 f_{12} f_2 + f_1^2 f_{22} \right)$$

For d^2y (-)

For $d^2y < 0$, it must be that $f_{11} f_2^2 - 2f_1 f_{12} f_2 + f_1^2 f_{22} < 0$

What gives us this? That restriction classifies a class of functions called "g.c."

QC = ^{that} the set of all points for which such a function takes on a value greater than any specific constant is a convex set.

Show pictures

We use a modified Hessian called the border Hessian.

Let $f(x_1, \dots, x_n)$

^{st.}
 $g(x_1, \dots, x_n) = 0$

loc. $f_i + \lambda g_i = 0$

SOC:

$$H_b = \begin{bmatrix} 0 & g_1 & g_2 & \dots & g_n \\ g_1 & f_{11} & f_{12} & \dots & f_{1n} \\ g_2 & f_{21} & f_{22} & \dots & f_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ g_n & f_{n1} & f_{n2} & \dots & f_{nn} \end{bmatrix}$$

For a max, SOC require the H_b ~~to~~ to be neg. def.

- ~~H_b~~
1. Princ. minor = < 0
 2. " " " = > 0

For a min, all princ. minors except 1st should be neg.

To show this is neg., load 2nd partials into matrix. ~~Concave by negative~~

Hessian matrix

1. Symmetric
2. Formed by all 2nd order partials of f_1 .

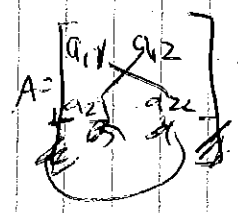
If f is continuous to twice diff of a vbls, its Hessian is:

$$H(f) = \begin{bmatrix} f_{11} & f_{12} & & f_{1n} \\ f_{21} & f_{22} & & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & & f_{nn} \end{bmatrix}$$

What we need to know if our 2-vbl f_1, f_2 is concave at the critical point. That in matrix language is the same as wanting to know if a matrix is pos. def. So, briefly, some matrix algebra

Determinant of a square matrix

1. notation: If A is matrix, $|A|$ is its det.
2. $|A|$ is some "scalar" or what we typically call in normal words "number" like 4 or 3.



$$|A| = (a_{11}a_{22} - a_{12}a_{21})$$

or

$$a_{11}a_{22} - a_{12}^2$$

3. pos. leading princ. minors of $n \times n$ square matrix A

one vbl series of det. of n rows & columns, where $n = 1, 2, \dots$. If A is 2×2 then:

1st princ. lead minor = a_{11}

2nd " " " " = $a_{11}a_{22} - a_{12}^2$

Lecture 3

1. Constrained Max
- Second order Conditions: Bordered Hessian to Q.C. Show pictures of 2, 1, 0 (p. 57)
- example of unconstrained to constrained.
2. Homogeneous Fn.
- definition of the "H^k"; $k=1$ and $k=0$ cases
- H^k derivative properties ex.
- Euler's Theorem
- Homothetic fn.
3. Preferences & Utility
- Axioms of RATS:
 - * Completeness
 - * Transitivity
 - * Continuity
- Utility or "Preference Function" (Tullock)
 - * ordinal vs. cardinal
 - * nonunique to monotonic transformations
 - * consumption to ceteris paribus
 - * Arguments of utility fn.
 - * Definition
 - * Visualize it w/ economic goods on 2-dim.
- Trades & Substitution
 - * Indifference Curves & the MRS (define)
 - * the map ("level surface")
 - * transitivity to non-transitivity on the map
 - * Convexity of the map.
 - * Behavior to convexity.
- Mathematical Derivation
 - * MRS from total diff of utility fn.
 - * Diminishing MRS - intuition to formal
 - * examples (i)
- Diff. Prefers are represented by diff. Utility fn.
 - * CD
 - * Perfect Subst.
 - * Perfect Complement
 - * CES utility

Homogeneous fn

$$f(x_1, \dots, x_n)$$

A fn. is said to be Homog. of degree K if:

$$f(tx_1, tx_2, \dots, tx_n) = t^K f(x_1, \dots, x_n)$$

- when $K=1$, then doubling its arguments by t doubles the value of the fn. itself
- when $K=0$, it'll have no effect.

H & Deriv

If a fn. f of degree K has order n , the partials of the fn. will be homog. of degree $K-1$.

$$\text{takes } f(tx_1, \dots, tx_n)$$

$$\frac{\partial}{\partial x_i} f(tx_1, \dots, tx_n) = t^{K-1} \frac{\partial f(x_1, \dots, x_n)}{\partial x_i}$$

or

$$f_i(tx_1, \dots, tx_n) = t^{K-1} f_i(x_1, \dots, x_n)$$

if $K=1$, then: (S & S)

$$f_i(tx_1, \dots, tx_n) = f_i(x_1, \dots, x_n)$$

partial derivatives are the same.

Euler's Theorem

Another useful feature of homogeneous functions can be shown by differentiating the definition for homogeneity w.r.t. proportionality factor, t . ~~Take this equation from ex/11/d:~~

$$f(tx_1, tx_2, \dots, tx_n) = t^k f(x_1, x_2, \dots, x_n)$$

Diff RHS w.r.t. t first:

$$\frac{d(\text{RHS})}{dt} = k t^{k-1} f(x_1, x_2, \dots, x_n)$$

Now the LHS:

$$\frac{d(\text{LHS})}{dt} = t \cdot f_1(tx_1, \dots, tx_n) + \dots + t f_n(tx_1, \dots, tx_n)$$

$$\frac{d(\text{LHS})}{dt} = x_1 f_1(tx_1, \dots, tx_n) + \dots + x_n f_n(tx_1, \dots, tx_n)$$

Set equal, & let $t=1$:

$$\boxed{k f(x_1, \dots, x_n) = x_1 f_1(x_1, \dots, x_n) + \dots + x_n f_n(x_1, \dots, x_n)}$$

("Euler's Theorem for homogeneous f_n ")

- What's it mean? For a homogeneous f_n , there is a definite rel. b/w the values of the function and the values of its partial derivatives.
- Several important economic rel. among f_n are based on this obs.
- "Discovering behavior w/ math" - Kind of cool.

Homothetic functions

defn: monotonic transformations preserve the order of the rel. b/w the arguments of a fn. to the value of that fn.

So, if a certain set of x 's yield larger values of y than a monotonic trans. will preserve that order of y .

ex: $f(x, y) = xy$

if we multiply ~~(x, y)~~ 2 , the xy combos will still cause $f(x, y)$ to move up or down in the same order as before.

$$\text{ex: } x=1, y=1, f(x, y)=1 \\ 2(xy) = 2 \cdot 1 = 2, f(x, y) = 2$$

$$x=2, y=1, f(x, y) = 2$$

$$2(xy) = 2 \cdot (2 \cdot 1) = 4 \quad \begin{matrix} 2 > 1 \\ 4 > 2 \end{matrix}$$

order preserved.

$$\text{or } f(x, y) = xy^2$$

But not $-1(xy)$.

Now higher xy give smaller values of $f(x, y)$!

take - implicit fn $f(x, y) = 0$ to total diff

$$f_x dx + f_y dy = 0$$

$$f_x dx = -f_y dy$$

$$\frac{dy}{dx} = -\frac{f_x}{f_y}$$

$$\boxed{\frac{dy}{dx} = -\frac{f_x}{f_y}}$$

If f is H^k , its partials are H^{k-1}

$$\frac{dy}{dx} = \frac{t^{k-1} f_x(tx, ty)}{t^{k-1} f_y(tx, ty)} = -\frac{f_x(tx, ty)}{f_y(tx, ty)}$$

Now let $t = 1/y$

$$\frac{dy}{dx} = -\frac{f_x\left(\frac{x}{y}, 1\right)}{f_y\left(\frac{x}{y}, 1\right)}$$

- Which shows that the tradeoff depends only on the ratio of x/y , not on their abs. values.
- If we apply any monotonic transformation ($F' > 0$) to the original Homothetic f , we have:

$$\frac{dy}{dx} = -\frac{F' f_x\left(\frac{x}{y}, 1\right)}{F' f_y\left(\frac{x}{y}, 1\right)} = -\frac{f_x\left(\frac{x}{y}, 1\right)}{f_y\left(\frac{x}{y}, 1\right)}$$

- Which means the monotonic transformation does not change the fact that $\frac{dy}{dx}$ is a fn. of just the ratios of x to y .

Axiom 3

Continuity

IF $A \sim B$, and fun

"situations close to A" are $\sim B$.

More of a mathematical assumption. It rules out knife-edge preferences that make it difficult to build a mathematical theory of choice.

Basically, if $A \sim B$, then $A + t > B + t$.
Helps us w/ transitivity.

Utility

- it is a function that shows a person ranking her preference over all situations from the least to the worst available.

* Mention Sister Theresa, Bertha, & Christian writer Piers.

Utility is not happiness, ~~happiness~~
or not exactly. It is preferences.

1. Nonuniqueness

Utility simply RANKS the order with numbers, which are the order value of the function.

$$\begin{aligned} U(A) &= 2 \\ U(B) &= 5 \end{aligned}$$

$$\begin{aligned} U(A) &= \text{~~2~~ 1} \\ U(B) &= 700 \text{ million} \end{aligned}$$

Same utility fun

Utility is unique only up to a monotonic transformation. So you could take a hairy utility fun like this, square it, & the analysis we do won't change.

$$\begin{aligned} U(x,y) &= f(x,y) = \sqrt{x+y} \\ U(x,y) &= [f(x,y)]^2 = x+y \end{aligned}$$

"Same utility fun"

Assign HW#1

2.1, 2.2, 2.3, 2.4

Due Tuesday next week.

Preferences & Utility.

Consumer theory is built on notion of utility, which is itself based on the idea of "preferences". We make 3 assumptions about people's preferences now. We say rational behavior is based on these assumptions about personal preferences.

Axiom 1: Completeness:

If A & B are any two situations, the individual can always specify exactly one of the two pass:

i. $A \succ B$

ii. $B \succ A$

iii. A & B are equally attractive.

SO: no indecision. They can completely make up their minds about the desirability of 2 alt. tell story of kids' indecision on which movie to watch. May not always be true. It is, though, an assumption.

Axiom 2:

Transitivity:

If $A \succ B$, and $B \succ C$, then $A \succ C$.

"internally consistent preferences."

money pump:

If you prefer $\text{\$ } 10$ to $\text{\$ } 5$ and $\text{\$ } 5$ to $\text{\$ } 1$ and $\text{\$ } 1$ to $\text{\$ } 10$

that would violate transitivity. That means $\text{\$ } 10$ is preferred to $\text{\$ } 10$.

Lecture 2 = max

1. ~~Program~~ Constrained max
 - a. Lagrangian
 - b. interpretation of λ
2. Duality
 - a. primal vs. dual prob.

ex: let $y = -x_1^2 + 2x_1 - x_2^2 + 4x_2 + 5$
 constraint:

pr. prob

$$\begin{aligned} \text{max}_{(x_1, x_2)} \quad & \mathcal{L} = -x_1^2 + 2x_1 - x_2^2 + 4x_2 + 5 + \lambda(1 + x_1 - x_2) \\ \text{FOC} \quad & \frac{\partial \mathcal{L}}{\partial x_1} = -2x_1 + 2 - \lambda = 0 \\ & \frac{\partial \mathcal{L}}{\partial x_2} = -2x_2 + 4 - \lambda = 0 \\ & \frac{\partial \mathcal{L}}{\partial \lambda} = 1 + x_1 - x_2 = 0 \end{aligned}$$

$$\lambda = \frac{2 - 2x_1}{2} = \frac{4 - 2x_2}{2}$$

~~$x_1 = 2 - x_2$~~
 ~~$x_1 = 1 - 2 + x_2$~~

$(1 + x_1 - x_2) - x_2 = 0$

$$\begin{aligned} 1 - [x_2 - 1] - x_2 &= 0 \\ 1 - x_2 - x_2 + 1 &= 0 \\ \frac{2}{2} &= \frac{2x_2}{2} \end{aligned}$$

$x_2^* = 1$

$$\begin{aligned} \lambda &= 2 - 2x_1^* \\ &= 2 - 2(0) \\ \lambda^* &= 2 \end{aligned}$$

$1 - x_1^* - 1 = 0$
 $x_1^* = 0$

$$\begin{aligned} y^* &= -(0)^2 + 2(0) - (1)^2 + 4(1) + 5 \\ &= 0 + 0 - 1 + 4 + 5 \\ y^* &= 8 \end{aligned}$$

$$\begin{aligned} 1 - x_1 &= 2 - x_2 \\ +x_2 & \\ \hline 1 - 2 + x_2 &= x_1 \\ x_2 - 1 &= x_1 \\ \boxed{x_1 = x_2 - 1} \end{aligned}$$

dual

max let $z = x_1 + x_2$ constraint is: $-x_1^2 + 2x_1 - x_2^2 + 4x_2 + 5 = 8$

$$\begin{aligned} \mathcal{L} &= x_1 + x_2 + \lambda(8 + x_1^2 - 2x_1 + x_2^2 - 4x_2 - 5) \\ \text{FOC} \quad & \frac{\partial \mathcal{L}}{\partial x_1} = 1 + \lambda(2x_1 - 2) = 0 \rightarrow \lambda(2x_1 - 2) = -1 \\ & \frac{\partial \mathcal{L}}{\partial x_2} = 1 + \lambda(2x_2 - 4) = 0 \\ & \lambda^* = \frac{-1}{2x_2 - 4} = \frac{1}{2}x_2 + \frac{1}{4} \\ & \lambda^* = \frac{1}{4} - \frac{1}{2}x_2 \end{aligned}$$

Second order Conditions w/ Unconstrained mv case

Let $y = f(x)$

$\frac{dy}{dx} = f'(x)$

$dy = f'(x) dx$

$d(dy) = f''(x) dx$

$d^2y = f''(x) dx^2$

For it to be a max, $d^2y < 0$, b/c it must be that at critical point, changing input causes slope of $\frac{dy}{dx}$ to fall, not rise. This requires that:

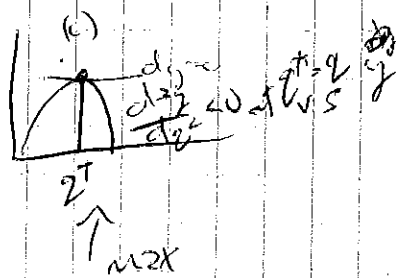
$f''(x) dx^2 < 0$

(1)

① we know $dx^2 > 0$, \therefore

\rightarrow (2) $f''(x) < 0$.

For one vbl, assuming $f''(x) < 0$ is sufficient. To have a "concave" shape at the critical point:



or

neither (a) or (b) is a max, though $\frac{dy}{dx} = 0$.