• We have previously explored the topics of (a.) local extrema and (b.) global (or absolute) extrema.

We have previously explored the topics of (a.) local extrema and (b.) global (or absolute) extrema. Each topic revolved around describing a function of several variables by the largest (or smallest) values it takes (a.) on a small open ball around a point P or (b.) on a domain.

- We have previously explored the topics of (a.) local extrema and (b.) global (or absolute) extrema. Each topic revolved around describing a function of several variables by the largest (or smallest) values it takes (a.) on a small open ball around a point P or (b.) on a domain.
- Using the Second Derivative Test, we were able to algorithmically generate data about the local extrema of a function f(x, y).

- We have previously explored the topics of (a.) local extrema and (b.) global (or absolute) extrema. Each topic revolved around describing a function of several variables by the largest (or smallest) values it takes (a.) on a small open ball around a point P or (b.) on a domain.
- Using the Second Derivative Test, we were able to algorithmically generate data about the local extrema of a function f(x, y).
- By the Extreme Value Theorem, we distinguished a nice class of functions and domains for which we could systematically describe the absolute extrema:

- We have previously explored the topics of (a.) local extrema and (b.) global (or absolute) extrema. Each topic revolved around describing a function of several variables by the largest (or smallest) values it takes (a.) on a small open ball around a point P or (b.) on a domain.
- Using the Second Derivative Test, we were able to algorithmically generate data about the local extrema of a function f(x, y).
- By the Extreme Value Theorem, we distinguished a nice class of functions and domains for which we could systematically describe the absolute extrema: **continuous** functions on **closed**, **bounded** domains achieve absolute extrema at critical or boundary points.

 Continuing our study of optimization, our next objective is to optimize a function of several variables subject to a constraint.

- Continuing our study of optimization, our next objective is to optimize a function of several variables subject to a constraint.
- Consider enjoying dinner at an Indian buffet with your family.

- Continuing our study of optimization, our next objective is to optimize a function of several variables subject to a constraint.
- Consider enjoying dinner at an Indian buffet with your family. Of course, the chicken tikka masala is absolutely delicious, but the naan is amazing, as well, and one can only eat so much.

- Continuing our study of optimization, our next objective is to optimize a function of several variables subject to a constraint.
- Consider enjoying dinner at an Indian buffet with your family. Of course, the chicken tikka masala is absolutely delicious, but the naan is amazing, as well, and one can only eat so much.
- **Question:** Could we use calculus to maximize the utility (satisfaction) we derive from our meal at the buffet given that we can only eat so much chicken tikka masala and naan?

- Continuing our study of optimization, our next objective is to optimize a function of several variables subject to a constraint.
- Consider enjoying dinner at an Indian buffet with your family. Of course, the chicken tikka masala is absolutely delicious, but the naan is amazing, as well, and one can only eat so much.
- **Question:** Could we use calculus to maximize the utility (satisfaction) we derive from our meal at the buffet given that we can only eat so much chicken tikka masala and naan?
- Of course, the answer is yes, and we achieve this optimization via the method of Lagrange multipliers.

• Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.

- Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.
- Consider walking along the curve g(x, y) = k and stopping at the first point Q where f(x, y) bumps into g(x, y) = k.

- Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.
- Consider walking along the curve g(x, y) = k and stopping at the first point Q where f(x, y) bumps into g(x, y) = k. We want to locate the point P at which f(x, y) is a maximum.

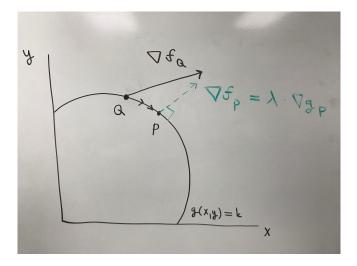
- Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.
- Consider walking along the curve g(x, y) = k and stopping at the first point Q where f(x, y) bumps into g(x, y) = k. We want to locate the point P at which f(x, y) is a maximum. We note that ∇f_Q points in the direction of the maximum increase of f, but perhaps we cannot move straight along ∇f_Q because we will fall off the constraint curve;

- Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.
- Consider walking along the curve g(x, y) = k and stopping at the first point Q where f(x, y) bumps into g(x, y) = k. We want to locate the point P at which f(x, y) is a maximum. We note that ∇f_Q points in the direction of the maximum increase of f, but perhaps we cannot move straight along ∇f_Q because we will fall off the constraint curve; however, if we move along g(x, y) = k in the direction of ∇f_Q , we will increase the value of f(x, y).

- Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.
- Consider walking along the curve g(x, y) = k and stopping at the first point Q where f(x, y) bumps into g(x, y) = k. We want to locate the point P at which f(x, y) is a maximum. We note that ∇f_Q points in the direction of the maximum increase of f, but perhaps we cannot move straight along ∇f_Q because we will fall off the constraint curve; however, if we move along g(x, y) = k in the direction of ∇f_Q, we will increase the value of f(x, y). Continuing to move along the constraint curve in the direction of ∇f_Q eventually leads to a point P at which ∇f_P is orthogonal to g(x, y) = k.

- Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.
- Consider walking along the curve g(x, y) = k and stopping at the first point Q where f(x, y) bumps into g(x, y) = k. We want to locate the point P at which f(x, y) is a maximum. We note that ∇f_Q points in the direction of the maximum increase of f, but perhaps we cannot move straight along ∇f_Q because we will fall off the constraint curve; however, if we move along g(x, y) = k in the direction of ∇f_Q , we will increase the value of f(x, y). Continuing to move along the constraint curve in the direction of ∇f_Q eventually leads to a point P at which ∇f_P is orthogonal to g(x, y) = k.

- Geometrically, the idea is very intuitive. We will assume that we wish to maximize a function f(x, y) subject to the constraint g(x, y) = k.
- Consider walking along the curve g(x, y) = k and stopping at the first point Q where f(x, y) bumps into g(x, y) = k. We want to locate the point P at which f(x, y) is a maximum. We note that ∇f_Q points in the direction of the maximum increase of f, but perhaps we cannot move straight along ∇f_{O} because we will fall off the constraint curve; however, if we move along g(x, y) = k in the direction of ∇f_Q , we will increase the value of f(x, y). Continuing to move along the constraint curve in the direction of ∇f_Q eventually leads to a point P at which ∇f_P is orthogonal to g(x, y) = k. Consequently, f(P) is a local maximum on g(x, y) = k. Considering that ∇g_P is orthogonal to the level curve g(x, y) = k at P, we conclude that ∇f_P and ∇g_P are parallel so that $\nabla f_P = \lambda \cdot \nabla g_P$.



MATH 127 (Section 14.8)

Given differentiable functions f(x, y) and g(x, y) such that f(x, y) has a local maximum (minimum) on the constraint curve g(x, y) = k at a point P = (a, b) and $\nabla g_P \neq (0, 0)$, there exists a nonzero scalar λ such that

$$\nabla f(a, b) = \lambda \cdot \nabla g(a, b),$$

i.e.,
$$f_x(a, b) = \lambda \cdot g_x(a, b)$$
 and $f_y(a, b) = \lambda \cdot g_y(a, b)$.

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume.

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume. Further, let us assume that our utility function is $u(x, y) = x^2y + xy^2$ and that we can only eat 24 ounces of food at the buffet,

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume. Further, let us assume that our utility function is $u(x, y) = x^2y + xy^2$ and that we can only eat 24 ounces of food at the buffet, i.e., our constraint function is given by v(x, y) = x + y = 24.

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume. Further, let us assume that our utility function is $u(x, y) = x^2y + xy^2$ and that we can only eat 24 ounces of food at the buffet, i.e., our constraint function is given by v(x, y) = x + y = 24. By the method of Lagrange multipliers, we maximize our utility at a point P such that $\nabla f_P = \lambda \cdot \nabla g_P$, i.e.,

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume. Further, let us assume that our utility function is $u(x, y) = x^2y + xy^2$ and that we can only eat 24 ounces of food at the buffet, i.e., our constraint function is given by v(x, y) = x + y = 24. By the method of Lagrange multipliers, we maximize our utility at a point P such that $\nabla f_P = \lambda \cdot \nabla g_P$, i.e.,

$$2xy + y^2 = \lambda;$$

2
$$2xy + x^2 = \lambda$$
; and

3 x + y = 24.

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume. Further, let us assume that our utility function is $u(x, y) = x^2y + xy^2$ and that we can only eat 24 ounces of food at the buffet, i.e., our constraint function is given by v(x, y) = x + y = 24. By the method of Lagrange multipliers, we maximize our utility at a point P such that $\nabla f_P = \lambda \cdot \nabla g_P$, i.e.,

$$1 \quad 2xy + y^2 = \lambda;$$

2
$$2xy + x^2 = \lambda$$
; and

3 x + y = 24.

By the third equation, we have that x = 24 - y so that $\lambda = 2(24 - y)y + y^2 = 48y - y^2$ by the first equation.

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume. Further, let us assume that our utility function is $u(x, y) = x^2y + xy^2$ and that we can only eat 24 ounces of food at the buffet, i.e., our constraint function is given by v(x, y) = x + y = 24. By the method of Lagrange multipliers, we maximize our utility at a point P such that $\nabla f_P = \lambda \cdot \nabla g_P$, i.e.,

$$1 \quad 2xy + y^2 = \lambda;$$

2
$$2xy + x^2 = \lambda$$
; and

3 x + y = 24.

By the third equation, we have that x = 24 - y so that $\lambda = 2(24 - y)y + y^2 = 48y - y^2$ by the first equation. By the second equation, we have that $\lambda = 2(24 - y)y + (24 - y)^2 = 576 - y^2$.

Back in our buffet example, let us denote by x and y respectively the amount of chicken tikka masala and naan we can consume. Further, let us assume that our utility function is $u(x, y) = x^2y + xy^2$ and that we can only eat 24 ounces of food at the buffet, i.e., our constraint function is given by v(x, y) = x + y = 24. By the method of Lagrange multipliers, we maximize our utility at a point P such that $\nabla f_P = \lambda \cdot \nabla g_P$, i.e.,

$$1 \quad 2xy + y^2 = \lambda;$$

2
$$2xy + x^2 = \lambda$$
; and

3 x + y = 24.

By the third equation, we have that x = 24 - y so that $\lambda = 2(24 - y)y + y^2 = 48y - y^2$ by the first equation. By the second equation, we have that $\lambda = 2(24 - y)y + (24 - y)^2 = 576 - y^2$. Comparing these equations gives 48y = 576 so that y = 12 = x.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, the method of Lagrange multipliers will always produce an absolute maximum or an absolute minimum.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, the method of Lagrange multipliers will always produce an absolute maximum or an absolute minimum.

(b.) False.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, the method of Lagrange multipliers will always produce an absolute maximum or an absolute minimum.

(b.) False. Consider the differentiable function f(x, y) = x and the differentiable curve g(x, y) = x - y = 0.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, the method of Lagrange multipliers will always produce an absolute maximum or an absolute minimum.

(b.) False. Consider the differentiable function f(x, y) = x and the differentiable curve g(x, y) = x - y = 0. We note that all points on the line y = x lie on the constraint curve;

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, the method of Lagrange multipliers will always produce an absolute maximum or an absolute minimum.

(b.) False. Consider the differentiable function f(x, y) = x and the differentiable curve g(x, y) = x - y = 0. We note that all points on the line y = x lie on the constraint curve; however, f(x, y) = x can be arbitrarily large or small, hence it has no absolute extrema.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, there exists a point P on the curve g(x, y) = k such that $\nabla f_P = \lambda \cdot \nabla g_P$ for some real number λ .

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, there exists a point P on the curve g(x, y) = k such that $\nabla f_P = \lambda \cdot \nabla g_P$ for some real number λ .

(b.) False.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, there exists a point P on the curve g(x, y) = k such that $\nabla f_P = \lambda \cdot \nabla g_P$ for some real number λ .

(b.) False. Consider the differentiable function f(x, y) = x and the differentiable curve $g(x, y) = (x - 1)^3 - y^2 = 0$.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, there exists a point P on the curve g(x, y) = k such that $\nabla f_P = \lambda \cdot \nabla g_P$ for some real number λ .

(b.) False. Consider the differentiable function f(x, y) = x and the differentiable curve $g(x, y) = (x - 1)^3 - y^2 = 0$. We have that $\nabla f = (1, 0)$ and $\lambda \cdot \nabla g = (3(x - 1)^2, -2y)$ are not equal at any point P on the curve g(x, y) = 0.

Given a differentiable function f(x, y) and a differentiable curve g(x, y) = k, there exists a point P on the curve g(x, y) = k such that $\nabla f_P = \lambda \cdot \nabla g_P$ for some real number λ .

(b.) False. Consider the differentiable function f(x, y) = x and the differentiable curve $g(x, y) = (x - 1)^3 - y^2 = 0$. We have that $\nabla f = (1, 0)$ and $\lambda \cdot \nabla g = (3(x - 1)^2, -2y)$ are not equal at any point P on the curve g(x, y) = 0. Explicitly, we must have that -2y = 0 so that y = 0. But this forces $(x - 1)^3 = 0$ so that x = 1 and $3(x - 1)^2 = 0$.