Indicate whether each statement is true (+) or false (o). If false, briefly state why or give a counterexample.

1. A barrier function adds a penalty to the objective when the solution approaches a boundary of the feasible region.
2. The number of "dependent" variables of the GRG algorithm is equal to the number of equality constraints.
3. The cubic interpolation procedure for one-dimensional minimization requires the computation of second derivatives.
4. The function $x^a$ is convex for $x > 0$.
5. The feasible directions algorithm computes a search direction by solving an LP.
6. The Fibonacci method for one-dimensional minimization requires the computation of derivatives.
7. If all posynomials in a (posynomial) GP problem are condensed into single terms, then it is always possible to rewrite the resulting problem as an LP problem.
8. A linear function is neither convex nor concave.
9. The Gradient Projection method always follows the boundary of the feasible region, and never enters the interior.
10. The logarithm of the dual GP objective $v(\delta, \lambda)$ above is a concave function of $\delta$ and $\lambda$.
11. The logarithm of the dual GP objective $v(\delta, \lambda)$ above is not a concave function of both $\delta$ and $\lambda$, but becomes so if you eliminate $\lambda_k$ using $\lambda_k = \sum_{i \in [k]} \delta_i$.
12. A locally optimal solution for a signomial geometric programming problem must be globally optimal.
13. The dual ("pseudo-dual") of a signomial GP problem may have multiple local maxima, but its global maximum will have the same objective value as the global minimum of the primal signomial GP.
14. Penalty functions may be used for both equality and inequality constraints, but barrier functions may be used only for inequality constraints.
16. If the Lagrangian function $L(x, \lambda)$ has a saddlepoint $(x^o, \lambda^o)$, then there is zero duality gap between primal and dual optimal solutions.

17. Consider the problem: $\min f(x)$ subject to $g_i(x) \leq 0, \ i=1,2,...,m, \ x \geq 0$ (where $g_i$ satisfy some constraint qualification) and its Lagrangian function

$$L(x, \lambda) = f(x) + \sum_{i=1}^{m} \lambda_i g_i(x)$$

Then if $f$ and $g_i$ are convex, the partial derivative of $L$ with respect to each $x_j$ must be zero at the optimum.

18. For the problem in the previous statement, $\lambda_i g_i(x)$ must be zero at the optimum.

19. For the problem in the previous statement, either $x_j$ or $\frac{\partial L(x, \lambda)}{\partial x_j}$ (or possibly both) must be zero at the optimum.

20. The limit, as $w \to 0$, of the function $(c/w)^w$ is $\infty$.

21. $\lim_{x \to 0} x \ln x = 0$.

22. If we define the function $\phi(x) = x \ln x$, then $\lim_{x \to 0} \frac{d\phi}{dx} = -\infty$.

23. When the dual problem is solved, the primal variables of a posynomial GP problem are often computed by exponentiating the Lagrange multipliers of the orthogonality constraints.

24. The function $f(x,y) = xy$ is a concave function of $x$ and $y$.

25. If an algorithm is applied to a minimization problem with optimal value zero, and the objective value is approximately halved at each iteration, then we would say that the algorithm has a linear rate of convergence.

26. The Hessian matrix of $(x^tQx + cx)$ is $2Q$.

27. In the QC/LD problem, the objective function is assumed to be quadratic.

28. If $f_i(x)$ is linear for $i=1,2,...,n$, then the function $F(x)$ defined by $F(x) = \max \{f_i(x); \ i=1,2,...,n\}$ is a convex function.

29. If a posynomial GP objective function continues to decrease as $x_j \to 0$ for some primal variable $x_j$, then the dual problem objective is unbounded.

30. If a posynomial GP objective function continues to decrease as $x_j \to +\infty$ for some primal variable $x_j$, then the dual problem is infeasible.

31. Every posynomial function is convex.

32. The dual of a constrained posynomial GP problem has only linear equality and nonnegativity constraints.
33. If a primal GP constraint is slack, then all the weights of the terms in that constraint must be zero.

34. In the QC/LD problem, the variables are restricted to be integer-valued.

35. The gradient of the function $f(x) = (x^t Qx + cx)$ is $Qx + c$.

36. Solving the QC/LD problem requires a one-dimensional search at each iteration.

37. The posynomial constraint $g_i(x) \leq 1$ has a convex feasible region.

38. It is always possible (e.g., by a change of variable) to reformulate a posynomial GP problem so as to have a convex objective and convex feasible region.

39. The objective of the posynomial GP problem, i.e.,

$$v(\delta, \lambda) = \prod_{i} \left( \frac{c_i}{\delta_i} \right)^{\delta_i} \prod_{k} \lambda_k^{\lambda_k}$$

is a concave function of $\delta$ and $\lambda$.

40. In the "Golden Section Search" method, more than one-third of the interval of uncertainty is eliminated at each iteration (assuming that no function values are equal).

41. If all posynomials in a (posynomial) GP problem are condensed into single terms, then the resulting problem has a feasible region which includes the original feasible region.

42. The Hessian matrix of a quadratic function is constant.

43. In Wolfe's complementary pivoting algorithm for QP, if a single artificial variable is used, then the tableau does not require an objective row.

44. The gradient projection method computes Lagrange multipliers at each iteration, and stops when they have the appropriate sign.

45. "Quasi-Newton" search methods for unconstrained minimization require the computation of second partial derivatives.

46. Newton's method for unconstrained minimization requires the computation of second partial derivatives.

47. If you guess at the value of some primal GP variable and then fix it at this value, the dual GP problem becomes more difficult to solve.

48. In a "generalized linear programming" problem, the column of coefficients of the variables must be selected as well as the variables.

49. The function $e^{ax}$ is convex only for $a \geq 0$.

50. The Davidon-Fletcher-Powell (DFP) algorithm requires the computation of partial derivatives.

51. If a posynomial function is "condensed" into a monomial, the monomial function (if not equal) is an overestimate of the posynomial function.
52. Wolfe's method for quadratic programming requires a one-dimensional search at every iteration.

53. If a constrained nonlinear programming problem satisfies a "constraint qualification", then a point which satisfies the Karush-Kuhn-Tucker conditions must be an optimal solution.

54. A barrier function allows a constraint to be violated, but adds a penalty if the constraint is violated.

55. The GRG algorithm requires the use of a one-dimensional search method.

56. The Feasible Directions algorithm requires the use of a one-dimensional search method.

57. If a constrained nonlinear programming problem satisfies a "constraint qualification", then the Karush-Kuhn-Tucker conditions must be satisfied by an optimal solution.

58. The function $e^{ax}$ is convex for all values of $a$.

59. In Wolfe's complementary pivoting method for quadratic programming, the complementary slackness conditions are satisfied after each iteration.

60. The tableau for Wolfe's method for quadratic programming includes columns for both primal and dual variables.

61. The function $x^a$ is convex for $a \geq 0$.

62. If a nonlinear programming problem has only linear constraints, then any point which satisfies the Karush-Kuhn-Tucker conditions must be optimal.

63. The Fletcher-Reeves method is also known as a "Quasi-Newton" method.

64. The quadratic interpolation procedure for one-dimensional minimization requires the computation of derivatives.

65. If the GRG algorithm were applied to a LP problem, it would produce, at each iteration, the same solution as the simplex algorithm for LP.

66. A penalty function allows a constraint to be violated, but adds a penalty if the constraint is violated.

67. The Lagrangian dual of a convex quadratic programming problem is a quadratic programming problem with only nonnegativity constraints on the dual variables.

68. Powell's algorithm for unconstrained minimization requires the computation of partial derivatives.

69. The Davidon-Fletcher-Powell method is also known as the "Conjugate Gradient" method.

70. In the QC/LD problem, the objective function is assumed to be convex.
Section B

Below is a list of references concerning Geometric Programming and applications. Part I lists papers which explicitly use GP, while Part II lists papers whose applications appear to be good candidates for GP.

Part I: Selected References to Geometric Programming Applications

56:271 Spring '97
D. Bricker


Questions:

a. Chose one reference from Part I of the list of GP applications.

b. Briefly summarize the application problem.

c. Write the mathematical model.

d. Identify the # of (primal) variables, # of constraints, total # of terms.

e. State whether posynomial or signomial in nature.

f. Describe the method used by the author(s) of the paper.

g. If sample data is given for a sample problem, or if you can guess at reasonable data, solve the GP problem.

Part II: Selected References to Potential Geometric Programming Applications


Name ___________________________
Questions:

a. Chose one reference from Part II of the list of potential GP applications.

b. Briefly summarize the application problem.

c. Write the mathematical model given by the author(s).

d. If possible, reformulate the model as a GP (either posynomial or signomial) problem.

e. Identify the # of (primal) variables, # of constraints, total # of terms.

f. Describe the method used by the author(s) of the paper.

g. If sample data is given for a sample problem, or if you can guess at reasonable data, solve the GP problem.