Advancements in Medical Statistics Promote Economies of Scale

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Introduction

Modern medical studies, especially those intended for high impact journals, can easily cost millions of dollars (USD). For example, cost of drug development, including phase I to III trials, averages about USD 800 million [1,2]. Studies searching for single nucleotide polymorphisms (SNPs) and copy number variants (CNVs) that contribute to disease are also costly. The full processing cost of an Affymetrix SNP 6.0 microarray, for example, can be $600 [3] multiplied by the 6000 to 9000 patients typical for recent high impact publications of Genome-Wide Association Studies (GWAS) [4-9]. Still, researchers aim for even larger sample sizes because clear answers of variants’ relationships with disease are not forthcoming given current sample sizes. For example, exome sequencing studies of 5300 and 6700 patients only yielded either very rare variants or variants with small effect size [10].

The burden of funding required for these studies strains the resources of even large pharmaceutical companies [4], wealthy corporations [13], and government funded groups, The Cancer Genome Atlas (TCGA) [14], the National Heart, Lung and Blood Institute and Exome Sequencing Project (ESP) [15], who host some of the largest current medical studies. To fund studies of increasing size, it is necessary to implement economies of scale. Economies of scale maintain or lower the cost per patient. Two studies accomplished this by inexpensive recruitment and follow-up by implementing a case-crossover design for their asthma study. Given typical recruitment difficulties, the larger the study, the more resources this design will save.

Advancements in medical statistics also increase economies of scale by increasing power and/or the number of feasible analyses without increasing patient size. Meta-analysis increases power with very little increase in cost by combining existing studies into a single dataset of larger patient size. Meta-analysis also makes additional analyses feasible, when in a single study these analyses either cannot be run or cannot reach statistical significance. Sandoval and Zarate [11] list these and six more ways that economy of scale is increased by meta-analysis.

Rogus et al. [16], Ketchum et al. [20], and Maetani and Gamel [12] increased the ability of their studies to achieve significant results without increasing cost. The advancement of Rogus et al. [16] was to use Monte Carlo resampling to correct for intra-subject correlation. This correlation kept their highly negative z-statistic from being significant despite the large number of subjects in the study. Maetani and Gamel [12] developed the Boag model in such a way that the expense of long-term follow-up is not necessary to predict the overall survival curve and the long-term effects of the measured variables in a study. Ketchum et al. [20] developed a within-subject normal-mixture model, minimizing costs by making only a few subjects necessary to obtain significant results. This was achieved by incorporating data from multiple tests per subject into the model. The model has accurate estimation with as few as 20 patients. It uses all the data and can include all covariates.

Several studies in this issue increase the number of potential analyses without increasing cost. The study design of Erbas et al. [19] allows more analyses than a case-control design study of the same size. Particularly, they had more power to detect interactions of time-related risk factors with asthma. Halabi [21] developed an adjustment for type I error rate that preserves the rate at the selected alpha level through multiple intermediate analyses. The adjustment also allows flexibility in the allocation of the type I error rate. In this way, the cost of the study is maintained while maximizing the study’s ability to detect meaningful changes. Also, the study becomes adaptable to intermediate discoveries without the need to make costly changes to the study or to design an entirely new study. Bergemann et al. [22] combined three test scores over four time points to make global normalized z-scores. These scores have more power, detecting significant differences at all time points when single test scores only detected significance in some time points. The global scores also yield lower p-values than in previous analyses.

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And they give the study better ability to describe longitudinal trends and determine the size of the difference between groups.

Discussion

The next major medical breakthroughs will likely be made in studies with many thousands of patients. To finance such studies and increase their potential for meaningful discoveries, they must have the study design and statistical methodology that maximize power and the ability to answer the question of interest. In other words, they must optimize economy of scale or these breakthroughs may be hindered by insufficient resources, such as money or patients. Medical statistics must continue to advance, as through the articles in this special issue, in order for major advancement to be made in most fields of medical research. It is encouraging that progress is being made on all fronts: increase in the detection of significance, increase in the sensitivity to pick up more accurate p-values, increase in the ability to perform more analyses with the same number of samples, and a decrease in the number of patients required to accomplish these advances. In conclusion, further advances in economics of scale must be made, especially in studies like GWAS, exome sequencing, and copy number detection, which search for rare biological occurrences.

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