Modeling (Multi-)Morbidity and (Poly-)Pharmacy in Outpatient Treatment with Gamma Distributions

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Keywords: Multimorbidity, Polypharmacy, Outpatient Treatment, Big Data, Gamma Distribution, Shannon Entropy.

Abstract: Polypharmacy is often directly causes by age and gender dependent multimorbidity. Todays treatment concepts, the individual decisions taken by physicians and the administration have to adress the complex needs of multimorbid patients. For modeling those phenomena on a collective level of an entire federal state a sufficiently large data repository is essential. The administrative bodies of the statutory health insurance in Germany have the data necessary and built up an extensive skill-set and inexpensive free-software tool-set for those evaluations. This study analyses the complete patient data of all outpatient treatments and drug prescriptions in Schleswig-Holstein (Northern German federal state) in the first quarter of 2017. Well adopted probability distributions for the frequency of diseases and drug groups decreasingly ordered within the classification system for all patients and age/gender partitions are estimated. Subsequently the levels of multimorbidity and polypharmacy (level of ICD-10/ATC-codes per quarter) are analysed in the same way. As a main result gamma distributions provide a well-adjusted model class for ICD and ATC code frequencies in the present very large routine dataset. The goodness-of-fit (full range of magnitudes of measurements) is much better than using mean values and variances.

1 INTRODUCTION

Multimorbidity and polypharmacy are major challenges for healthcare systems cf. (Dormann, H., Sonst, F., Vogler, R., Patapovas, A., Pfistermeister, B., Plank-Kiegle, B., Kirchner, M., Hartmann, N., Burke, T. Maas, R., 2013; Fortin, M., Hudon, C., Haggerty, J., Akker, M., Almirall, J., 2010; Islam, M. M., Valderas, J. M., Yen, L., Dawda, P., Jowsey, T., McRae, I. S., 2014; Jeschke, E., Ostermann, T., Vollmar, HC, Tabali, M., Matthes, H., 2012; Glynn, L.G., Valderas, J.M., Healy, P., Burke, E., Newell, J., Gillespie, P., Murphy, A. W., 2011; Maher, R. L., Hanlon, J., Hajjar, E. R., 2014). Polypharmacy can also increase the risk of non-adherence, resulting in a suboptimal medication effectiveness and clinical consequences cf. (Glynn, L.G., Valderas, J.M., Healy, P., Burke, E., Newell, J., Gillespie, P., Murphy, A. W., 2011). If the medication non-adherence is not identified by the provider, they either increase the initial dose or add a second agent which in turn raises the health care costs and risk of adverse drug events cf. (Jeschke, E., Ostermann, T., Vollmar, HC, Tabali, M., Matthes, H., 2012). The frequency distributions for very large populations (big data) are still mostly unknown because most publications consider special diseases with sample sizes of a few hundred and up to thousand patients. Register Studies usually address special aspects with density distribution analysis cf. (Johnell, K., Klarin, I., 2007). The geriatric population is an example for high prevalence of polypharmacy associated with multiple comorbidities and advanced age cf. (Subeesh, V. K.,...
Shivaskankar, V., Gouri, N., Sriram, S., 2015; Subeesh, V. K., Gouri, N., Beulah, E. T., Shivaskankar, V., 2017). In this paper the number of different diagnoses and drug groups at certain code levels are considered as multimorbidity and polypharmacy levels for patients and the related statistical distributions are analyzed. The same approach is taken for code frequencies. In 2017 the statutory health insurances and the associated physicians in the German federal state of Schleswig-Holstein launched expenditure controlling of outpatient prescriptions by morbidity related groups (MRG) cf. (Schuster, R., Emcke, T., Arnstedt, E.v., Heidbreder, M., 2016; Emcke, T., Ostermann, T., v. Arnstedt, E., Heidbreder, M., 2017; Schuster, R., Ostermann, T., Heidbreder, M., Emcke, T., 2018). By looking for the group with the highest drug costs on the third level ATC (four characters) within a quarter for each consulted physician and a certain patient the MRG setting takes the patient level into account. In a previous study the relations of the drug based MRG groups and diagnoses of the patients were analyzed using an age and gender standardization cf. (Schuster, R., Emcke, T., Arnstedt, E.v., Heidbreder, M., 2016). In the present analysis the density distributions of multimorbidity and polypharmacy as well as the ordered frequency of cases with certain ICD-10 and ATC codes are modeled by gamma distributions.

2 METHODS

We analyze all treatments and prescriptions of physicians for patients of the statutory health insurance (SHI) by SHI physicians in Schleswig-Holstein in the first quarter of 2017 without age restrictions. The analysis is patient-centered, meaning that the datasets of all treatments and prescriptions of all physicians with respect to a patient are used. The dataset covers 2,044,690 patients and 1,411,087 patients with drug prescriptions, and a pseudonymized patient ID with age and gender information. We utilize the three-character level of International Statistical Classification of Diseases and Related Health Problems [ICD]. The same diagnoses for the same patient by different physicians are not counted repeatedly. For prescription analysis the International Anatomic Therapeutic Chemical (ATC) classification system with German specifications provided by the German Institute of Medical Documentation and Information (DIMDI) is used. We analyze drug groups given by the four digit ATC (third level). The traditional approach uses summary statistics of observations, such as mean or variance, in order to find most likely probability distributions using the maximum entropy method. Frank and Smith cf. (Frank, A. S., Smith, D.E., 2010) extended this method by incorporating information about the scale of measurement. A gamma distribution has a power law shape for small magnitudes and changes to an exponential shape for large magnitudes. The scale information is included by a constraint for the maximum entropy given by an interpolation between the linear and geometric mean.

The hardware used to extract and link the data/master data is a dedicated Debian GNU/Linux Server [current generation Intel i7, 16 GByte RAM] administered by the Medical Advisory board of Statutory Health Insurance in Northern Germany. It runs a LAMP configuration (Debian GNU/Linux, Apache 2.4.29, Maria DB 10.3 [extensive use of partitioning] and PHP 7.3 [with PEAR framework esp. for spreadsheet output]).

The coding was done using the Perl programming language and the command-line tools sed/sort/awk for quick-prototyping tasks. For the statistical analysis we used Mathematica by Wolfram Research in order to get a curve fitting to a Gamma distribution for ICD and ATC drug group frequencies as well as for multimorbidity and polypharmacy frequencies. The Wolfram language and Mathematica are free when used on the small single-board computer Raspberry Pi (eg. Raspberry Pi 3 - Model B: 1,2 Ghz Quadcore - 1 GByte RAM).

The inexpensive open source/free software setup makes the cooperation of different administrative bodies possible. At the moment the hard- and software setup is able to process the data of about 6-10 Million patients.

3 RESULTS

On average the patients have 7.7 diseases at three-character ICD level (figure 1).
Patients with drug prescriptions on average have 3.2 drug groups at four digit ATC (3rd level) (figure 2).

Figure 2: Age and gender dependent polypharmacy (mean values).

The curve fit to a gamma function gives the shape value of 0.4366 (0.5404) for males (females) and a decline value of 349.7 (223.0) for males (females). For women the curve fit gets worse for the most frequently used diagnoses, this effect is much weaker in men. With even smaller differences, the opposite can be stated for drug groups. This gives a shape value of 0.07833 (0.7710) for males (females) and a decline value of 24.94 (27.88) for males (females). The fit of the gamma distribution curves in figures 7, 8, 9 and 10 is much more exact with respect to multimorbidity and polypharmacy level (number of different codes) compared to the classification codes (ICD/ATC) considered in figures 3, 4, 5 and 6.

The ICD shape parameter is 1.0502 (0.9537, 1.1657) [total (male, female)] and the decline parameter has the value 6.798 (6.3856, 6.7730). The ATC shape parameter is 0.9679 (0.9982, 0.9458) and the decline parameter has the value 2.833 (2.7098, 2.8658).

The age depended mean values for the number of diagnoses (multimorbidity level) and the number of drug groups (polypharmacy level) show more gender
Looking at the Top ATC/ICD positions the gender differences with respect to diagnoses than polypharmacy.

The only drug-classes where male prescriptions outweigh are ace-inhibitors, lipid modifying agents and antitrombotic drugs. In part this can be explained by the ranking and distribution of ICD-10 codes in Figure 12.

But only the good modeling results of the gamma-

Figure 8: Curve fit for multimorbidity level (number of codes) and large magnitudes (data (blue), gamma fit (red)).

Figure 9: Curve fit for multimorbidity level (number of codes) and small magnitudes (data (blue), gamma fit (red)).

Figure 10: Curve fit for multimorbidity level (number of codes) and large magnitudes (data (blue), gamma fit (red)).

distribution approach enable a sound age-dependent computation of the decline as well as shape parameters for e.g. diagnoses (figures 13 and 14):

Figure 11: Top ATC positions (3rd level) by gender.

Figure 12: Top ICD positions (3-character level) by gender.

Figure 13: Age dependent decline parameter (diagnoses).

Figure 14: Age dependent shape parameter (diagnoses).
Additionally the corresponding age dependent Shannon Entropies for diagnoses and drug prescriptions are determined (figures 15 and 16):


