July 2-5, 2017 London, United Kingdom



Association for Computing Machinery

Advancing Computing as a Science & Profession

DH'17

Proceedings of the 2017 International Conference on **Digital Health**

In cooperation with: ACM SIGKDD & ICPS

Supported by:

UCL Institute for Risk & Disaster Reduction, UCL Grand Challenges, Frontiers in Digital Health, International Society for Telemedicine & eHealth, Mad*Pow, Digital Catapult, UK Science & Innovation Network, UCL Global Engagement Office and Enterprise Europe Network

DH 2017 Conference Organization

| General and Scientific Chair: | Patty Kostkova (University College London) |
|-------------------------------|----------------------------------------------------------------------------------------------------------------------------|
| Programme Co-Chairs: | Floriana Grasso (University of Liverpool) |
| | Carlos Castillo (Eurecat) |
| | Yelena Mejova (QCRI) |
| | Arnold Bosman (Transmissible) |
| Local and Comms Chair: | Patrizia Isabelle Duda (IRDR, UCL; WADEM) |
| Poster and Demo Chair: | Andreea Molnar (University of Portsmouth) |
| Web and Proceedings Chair: | Andrew Roxburgh (University of Liverpool) |
| PhD Track Chair: | Yelena Mejova <i>(QCRI)</i> |
| Business Chair: | Sarah Schubert (IRDR, University College London) |
| Coordinator: | Emma Defoe (University College London) |
| Senior Programme Committee: | Philip Abdelmalik (Public Health Agency of Canada) |
| | Bruria Adini (Tel Aviv University) |
| | Eyhab Al-Masri (University of Waterloo) |
| | Alain April (École de Technologie Supérieure) |
| | Jakob E. Bardram (<i>Technical University of Denmark</i>) |
| | Isaac Bogoh (University of Toronto) Pamela Briggs (Northumbria University) |
| | Nigel Collier (University of Cambridge) |
| | Simon de Lusignan (University of Surrey) |
| | Dustin Ditommaso (<i>Mad*Pow</i>) |
| | Richard Dobson (<i>King's College London and UCL</i>) |
| | Claudio Eccher (<i>FBK-IRST</i>) |
| | Baltasar Fernández Manjón (Universidad Complutense de Madrid) |
| | Pietro Ghezzi (Brighton & Sussex Medical School) |
| | Hamed Haddadi (<i>Queen Mary University of London</i>) |
| | David Harper (Chatham House) |
| | Dionisio Herrera (TEPHINET) |
| | Jeroen Jansen (<i>Evidence Aid</i>) |
| | Ilan Kelman (University College London) |
| | Aileen Kitching (EPIET Alumni Network (EAN)) |
| | Alex Matic (<i>Telefonica Research</i>) |
| | Eric Meyer (University of Oxford) |
| | Nuria Oliver (<i>DataPopAlliance</i>) Hans C. Ossebaard (<i>University of Twente/Health care Quality Institute</i>) |
| | Daniela Paolotti (ISI Foundation) |
| | Michal Rosen-Zvi (<i>IBM</i>) |
| | Alberto Sanna (Scientific Institute San Raffaele) |
| | Michele Tizzoni (ISI Foundation) |
| | Erik van der Goot (European Commission's Joint Research Centre) |

| Programme Committee: | Harshavardhan Achrekar (University of Massachusetts Lowell) |
|----------------------|------------------------------------------------------------------------------|
| | Akram Alomainy (Queen Mary University of London) |
| | Nadia Berthouze (University College London) |
| | Olivier Bodenreider (US National Library of Medicine) |
| | Celia Boyer (<i>Health On the Net Foundation</i>) |
| | Miroslav Bursa (Czech Technical University in Prague) |
| | Elena Cardillo (Institute for Informatics and Telematics, Italian National |
| | Council of Research) |
| | Robin Cohen (U Waterloo) |
| | Mike Conway (University of Utah) |
| | Olivier Corby (INRIA) |
| | Ulises Cortés (Universitat Politècnica de Catalunya / Barcelona |
| | Supercomputing Center) |
| | Jean Costa (Cornell University) |
| | Aaron Crandall (Washington State University) |
| | Aron Culotta (Illinois Institute of Technology) |
| | Mary Czerwinski (Microsoft Research) |
| | Karen Day (University of Auckland) |
| | Berardina Nadja De Carolis (dipartimento di informatica universita' di bari) |
| | Gayo Diallo (ISPED & LABRI, University of Bordeaux) |
| | Jim Duggan (National University of Ireland, Galway) |
| | Michael Edelstein (Chatham House) |
| | Luis Fernandez Luque (Qatar Computing Research Institute) |
| | Edward Fottrell (UCL Institute for Global Health) |
| | Ana Franco (Instituto Gulbenkian de Ciência) |
| | Reva Freedman (Northern Illinois University) |
| | Amira Ghenai (University of Waterloo) |
| | Christophe Giraud-Carrier (Brigham Young University) |
| | Natalia Grabar (STL CNRS Université Lille 3) |
| | Cathal Gurrin (Dublin City University) |
| | Jaap Ham (Eindhoven University of Technology) |
| | Asha Herten-Crabb (Chatham House) |
| | Helmut Horacek (Saarland University) |
| | Muhammad Imran (<i>Qatar Computing Research Institute</i>) |
| | Simon Kamronn (Technical University of Denmark) |
| | Matthew Kay (University of Washington) |
| | Jeonggil Ko (Ajou University) |
| | Spyros Kotoulas (IBM Research) |
| | Vasileios Lampos (University College London) |
| | Toby Lasserson (Cochrane) |
| | Marilyn Lennon (University of Glasgow) |
| | Lenka Lhotska (Czech Technical University in Prague, Dept. of Cybernetics) |
| | Nut Limsopatham (Univeristy of Cambridge) |
| | Peter Lucas (Radboud University Nijmegen) |
| | Jochen Meyer (OFFIS Institute for Information Technology) |
| | Francesco Miele (Bruno Kessler Foundation - Center for Communication |
| | and Information Technology) |
| | Antonio Moreno (URV) |
| | |

| Programme Committee | |
|-----------------------|---------------------------------------------------------------------------------------------------------------------------|
| (continued): | Bobak Mortazavi (Texas A&M Center for Remote Health Technologies |
| | and Systems) |
| | Nikki Newhouse (University College London) |
| | Rita Orji (University of Saskatchewan) |
| | Michal Ozery-Flato (IBM Haifa Research lab) |
| | Heather Patrick (Carrot Sense) |
| | Pasi Penttinen (ECDC) |
| | Ming-Zher Poh (Cardiio, Inc.) |
| | Matthew Purver (Queen Mary University of London) |
| | Luz Rello (Carnegie Mellon University) |
| | David Riaño (Universitat Rovira i Virgili) |
| | Britta Ricker (University of Washington Tacoma) |
| | Sara Rubinelli (University of Lugano) |
| | Carlos Luis Sánchez Bocanegra (University of Seville) |
| | Melina Santos (Ministry of Health of Brazil) |
| | Heiko Schuldt (University of Basel) |
| | Uri Shalit (New York University) |
| | Tomer Simon (<i>Ready.org.il</i>) |
| | Steven Simske (Hewlett-Packard Labs) |
| | Aneesha Singh (UCL Interaction Centre) |
| | Kirsten Smith (University of Southampton) |
| | Katarzyna Stawarz (University of Bristol) |
| | Charlotte Tang (University of Michigan Flint) |
| | Adel Taweel Matthews F. Taylor (Washington State University) |
| | Matthew E. Taylor (Washington State University) |
| | Ielka Van Der Sluis (University of Groningen) |
| | Kathleen Vancleef <i>(Newcastle University)</i> Krishna K. Venkatasubramanian <i>(Worcester Polytechnic Institute)</i> |
| | Nervo Verdezoto (University of Leicester) |
| | Silja-Riin Voolma (University of Cambridge) |
| | Katarzyna Wac (University of Geneva) |
| | Jessica Wardlaw (University of Nottingham) |
| | Ingmar Weber (<i>Qatar Computing Research Institute</i>) |
| | Sarah Wiseman (Goldsmiths, University Of London) |
| | Yeliz Yesilada (University of Manchester) |
| | Qian Zhang (Northeastern University) |
| Additional Reviewers: | Alexandra Balahur (European Commision's Joint Research Centre) |
| | Jo Gibbs (UCL Interaction Centre) |
| | Sakib Jalil (University of Saskatchewan) |
| | Laura König (Universität Konstanz) |
| | Richard Lomotey (University of Saskatchewan) |
| | Michaela Reisinger (Austrian Institute of Technology) |
| | Beatrix Zechmann (Austrian Institute of Technology) |
| | Simo Zhang (Northeastern University) |
| | |

Table of Contents

| DH2017 Conference Organizationix | | | |
|----------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|--|
| D | H2017 Sponsors and Partners | | |
| Se | ession: Digital Tools in Practice | | |
| • | (How) do People Negotiate Online Information into their Decision Making with Healthcare Professionals? | | |
| • | Are HIV Smartphone Apps and Online Interventions Fit for Purpose? | | |
| • | Towards an Ontology to Identify Barriers to Physical Activityfor Type 2 Diabetes | | |
| • | Snake Alert Application: A Snake Tracking & Reporting System | | |
| Se | ession: Online Communities | | |
| • | The Current State of Online Social Networking for the Health Community: Where Trust Modeling Research May Be of Value | | |
| • | Analysis of Smoking and Drinking Relapse in an Online Community | | |
| • | Exploring the Preferences of Female Teenagers when Seeking Sexual Health Information using Websites and Apps | | |
| • | Who is Spreading Rumours about Vaccines? Influential User ImpactModelling in Social Networks48Patty Kostkova, Vino Mano (University College London),Heidi J. Larson, William S. Schulz (London School of Hygiene & Tropical Medicine) | | |
| Se | ession: Modeling Disease | | |
| • | Speech-based Diagnosis of Autism Spectrum Condition by Generative Adversarial Network Representations 53 Jun Deng, Nicholas Cummins, Maximilian Schmitt (University of Passau), 53 Kun Qian (Technische Universität München), Fabien Ringeval (Université Grenoble Alpes), 53 Björn Schuller (Imperial College London & University of Passau) 53 | | |
| • | Classification of Visit-to-Visit Blood Pressure Variability: A Machine Learning Approach for Data Clustering on Systolic Blood Pressure Intervention Trial (SPRINT) | | |
| • | On Consolidated Predictive Model of the Natural History of Breast Cancer: Primary Tumor and Secondary Metastases in Patients with Lymph Nodes Metastases | | |
| • | Improving RNN with Attention and Embedding for Adverse Drug Reactions | | |

Session: Study Methodologies

| • | Conflict Discovery and Analysis for Clinical Trials Bonnie MacKellar, Christina Schweikert (<i>St. John's University</i>) | 72 |
|----|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| • | A Case Study of Anonymization of Medical Surveys Michele Gentili, Sara Hajian, Carlos Castillo (<i>Eurecat - Technology Centre of Catalonia</i>) | 77 |
| • | Rapid Methods to Assess the Potential Impact of Digital Health Interventions, and their Application to Low Resource Settings Geoff Royston (Independent) | 82 |
| • | Using Data Mining to Refine Digital Behaviour Change Interventions Nathaniel Charlton (University of Brighton & Do Something Different Ltd), John Kingston (University of Brighton), Miltos Petridis (Middlesex University), Ben C. Fletcher (University of Hertfordshire & Do Something Different Ltd) | 90 |
| • | A Regularization Approach for Identifying Cumulative Lagged Effects in Smart Health Applications Karthik Srinivasan, Faiz Currim, Sudha Ram, Matthias R. Mehl, Casey Lindberg, Esther Sternberg, Perry Skeath (<i>University of Arizona</i>), Davida Herzl, Reuben Herzl, Melissa Lunden, Nicole Goebel, Scott Andrews (<i>Aclima Inc.</i>), Bijan Najafi, Javad Razjouyan, Hyo-Ki Lee (<i>Baylor College of Medicine</i>), Brian Gilligan, Judith Heerwagen, Kevin Kampschroer, Kelli Canada (U. S. General Services Administration) | 99 |
| Se | ession: Social Media | |
| • | Classifying Information from Microblogs during Epidemics Koustav Rudra, Ashish Sharma, Niloy Ganguly (<i>Indian Institute of Technology, Kharagpur</i>), Muhammad Imran (<i>Qatar Computing Research Institute</i>) | 104 |
| • | Enhancement of Epidemiological Models for Dengue Fever Based on Twitter Data Julio Albinati, Wagner Meira Jr, Gisele L. Pappa, Mauro Teixeira, Cecilia Marques-Toledo (<i>Universidade Federal de Minas Gerais</i>) | 109 |
| • | Discovering Potential Effects of Dietary Supplements from Twitter Data | 119 |
| • | Emotional and Linguistic Cues of Depression from Social Media Nikhita Vedula, Srinivasan Parthasarathy (<i>Ohio State University</i>) | 127 |
| Se | ession: Health Systems & Tools | |
| • | An Interactive Web-based Decision Support System for Mass Dispensing, Emergency Preparedness, and Biosurveillance Eva K. Lee (Georgia Institute of Technology), Ferdinand H. Pietz (Centers for Disease Control and Prevention), Chien-Hung Chen, Yifan Liu (Georgia Institute of Technology) | 137 |
| • | Risk Factors Linked to Influenza-like Illness as Identified from the Mexican Participatory Surveillance System Reporta": Risk Factors in ILI" Christopher R. Stephens (Universidad Nacional Autonoma de Mexico), Rocio Rodríguez-Ramírez (Intellego Business Intelligence), Victor Mireles, Sergio Hernández-López, Concepción Garcia-Aguirre, Juan Arturo Herrera-Ortiz, Natalia B. Mantilla-Berniers (Universidad Nacional Autonoma de Mexico) | 147 |
| • | A Low-cost Adaptable and Personalized Remote Patient Monitoring System Eva Lee, Yuanbo Yu (Georgia Institute of Technology), Robert Davis, Brent Egan (University of South Carolina School of Medicine) | 155 |

| • | Towards Health (Aware) Recommender Systems . Hanna Schäfer (<i>Technical University of Munich</i>), Santiago Hors-Fraile (<i>University of Seville</i>), Raghav Pavan Karumur (<i>University of Minnesota</i>), André Calero Valdez (<i>RWTH Aachen University</i>), Alan Said (<i>University of Skövde</i>), Helma Torkamaan (<i>University of Duisburg-Essen</i>), Tom Ulmer (<i>FHS St. Gallen</i>), Christoph Trattner (<i>MODUL University Vienna</i>) | . 157 |
|----|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|
| • | Big MRI Data Dissemination and Retrieval in a Multi-Cloud Hospital Storage System Antonino Galletta (<i>University of Messina & IRCCS Centro Neurolesi</i>), Antonio Celesti (<i>University of Messina</i>), Francesco Tusa (<i>University College London</i>), Maria Fazio (<i>University of Messina</i>), Placido Bramanti (<i>IRCCS Centro Neurolesi</i>), Massimo Villari (<i>University of Messina</i>) | . 162 |
| Se | ession: Health Data Mining | |
| • | Using Machine Learning for Automatic Identification of Evidence-Based Health Information on the Web | 167 |
| | Majed M. Al-Jefri, Roger Evans (University of Brighton, Moulsecoomb), Pietro Ghezzi (University of Sussex, Falmer), Gulden Uchyigit (University of Brighton, Moulsecoomb) | . 107 |
| • | CCS Coding of Discharge Diagnoses via Deep Neural Networks Chadi Helwe, Shady Elbassuoni, Mirabelle Geha, Eveline Hitti, Carla Makhlouf Obermeyer <i>(American University of Beirut)</i> | . 175 |
| • | Extracting Gene-Disease Relations from Text to Support Biomarker Discovery Paul Thompson, Sophia Ananiadou (<i>University of Manchester</i>) | . 180 |
| • | Data Mining and Time-Series Analysis as Two Complementary Approaches to Study Body Temperature in Obesity Ruben Fossion, Christopher R. Stephens, Karla P. García-Pelagio, Lorena García-Iglesias (Universidad Nacional Autonoma de Mexico) | . 190 |
| • | Automatic Extraction of Deep Phenotypes for Precision Medicine in Chronic Kidney Disease Prerna Singh (Johns Hopkins University), Varun Chandola, Chester Fox (University at Buffalo, State University of New York) | . 195 |
| Se | ession: Wearables | |
| • | FitBit Garden: A Mobile Game Designed to Increase Physical Activity in Children | . 200 |
| • | A Wearable Motion Tracking System to Reduce Direct Care Worker Injuries: | 000 |
| | An Exploratory Study Jonathan Muckell, Yuchi Young, Mitch Leventhal (University at Albany) | . 202 |
| • | Personal Wearable Devices to Measure Heart Rate Variability: A Framework of Cloud Platform for Public Health Research | . 207 |
| Se | ession: Games for Health | |
| • | MHealth Games as Rewards: Incentive or Distraction? Kevin Gary, Ryan Stoll, Pooja Rallabhandi, Mandar Patwardhan, Derek Hamel, Ashish Amresh, Armando Pina (<i>Arizona State University</i>), Kevin Cleary (<i>Children's National Health System</i>), Zenaide Quezado (<i>National Institutes of Health</i>) | . 209 |
| • | Towards a Gamified Recommender System for the Elderly Madita Herpich, Thomas Rist (<i>Hochschule Augsburg</i>), Andreas Seiderer, Elisabeth André (<i>Universität Augsburg</i>) | . 211 |
| • | Analysis of Soft Data for Mass Provision of Stereoacuity Testing Through a Serious Game for Health Gary Ushaw, Craig Sharp, Jessica Hugill, Sheima Rafiq, Carla Black, Therese Casanova, Kathleen Vancleef, Jenny Read, Graham Morgan <i>(Newcastle University)</i> | . 216 |

PhD Session

| A | uthor Index | 243 |
|---|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|
| • | Screening for Neonatal Jaundice with a Smartphone Felix Outlaw (University College London), Judith Meek (University College London Hospitals Trust), Lindsay W. MacDonald, Terence S. Leung (University College London) | 241 |
| • | Development of a Multi-Device Nutrition Logging Prototype Including a Smartscale Andreas Seiderer, Elisabeth André (<i>Augsburg University</i>) | 239 |
| • | Personal Health Records: Understanding the Factors that Contribute to Creating Value and Practical use by Patients and Citizens Irina Osovskaya (University College London) | 237 |
| • | Health Misinformation in Search and Social Media Amira Ghenai (University of Waterloo) | 235 |
| • | Learning Human Interaction using a Smart Rollator, the <i>i</i>-Walker Atia Cortés (Universitat Politècnica de Catalunya) | 233 |
| • | Preventing Frail and Elderly Hospital Admissions: Developing an Evaluation Framework for the 'Closer to Home' Quality Improvement Programme in NHS Forth Valley Maria Cristina Martin, Matt-Mouley Bouamrane, Kimberly Kavanagh (<i>University of Strathclyde</i>), Paul Woolman (<i>NHS Forth Valley</i>) | 231 |
| • | The Public Health Potential of the Current Health Apps for Increasing Physical Activity Paulina Bondaronek, Elizabeth Murray, Fiona Hamilton <i>(University College London)</i> | 229 |
| • | Symptom or Sentiment? Considerations for mHealth Interventions Designed for HIV+ Adolescents Craig R. Carty (University of Oxford), Rebecca Hodes (University of Cape Town), Lucie Cluver (University of Oxford), Sanjana Bhardwaj (UNICEF South Africa) | 227 |
| • | GENOMEVIEWER: An Interactive Genomic Somatic Mutation Visualizer. Beatriz Kanzki, Alain April (École de Technologie Supérieure) | 225 |
| • | Text Mining from Social Media for Public Health Applications Joana M. Barros (<i>National University of Ireland - Galway</i>) | 223 |
| • | (Bio)medical Publications in the Age of Big Data: Yes, They Are Different | 221 |

On Consolidated Predictive Model of the Natural History of Breast Cancer: Primary Tumor and Secondary Metastases in Patients with Lymph Nodes Metastases

Ella Y. Tyuryumina National Research University Higher School of Economics Moscow, Russia eyatyuryumina@gmail.com Alexey A. Neznanov National Research University Higher School of Economics Moscow, Russia aneznanov@hse.ru

ABSTRACT

This paper is devoted to mathematical modelling of the progression and stages of breast cancer. The âĂIJConsolidated mathematical growth Model of primary tumor (PT) and secondary distant metastases (MTS) in patients with lymph nodes MTS (Stage III)" (CoM-III) is proposed as a new research tool. The CoM-III rests on an exponential tumor growth model and consists of a system of determinate nonlinear and linear equations. The CoM-III describes correctly primary tumor growth (parameter T) and distant metastases growth (parameter M, parameter N). The CoM-III model and predictive software: a) detect different growth periods of primary tumor and distant metastases in patients with lymph nodes MTS; b) make forecast of the period of the distant metastases appearance in patients with lymph nodes MTS; c) have higher average prediction accuracy than the other tools; d) can improve forecasts on survival of breast cancer and facilitate optimisation of diagnostic tests. The CoM-III enables us, for the first time, to predict the whole natural history of PT and secondary distant MTS growth of patients with/without lymph nodes MTS on each stage relying only on PT sizes.

CCS CONCEPTS

• Applied computing \rightarrow Consumer health; Health informatics; • Mathematics of computing \rightarrow Solvers;

KEYWORDS

breast cancer; mathematical modelling; exponential model; primary tumor; secondary metastases; lymph nodes metastases; survival; predictor

ACM Reference format:

Ella Y. Tyuryumina and Alexey A. Neznanov. 2017. On Consolidated Predictive Model of the Natural History of Breast Cancer: Primary Tumor and Secondary Metastases in Patients with Lymph Nodes Metastases. In *Proceedings of DH '17, London, United Kingdom, July 2–5, 2017,* 7 pages. https://doi.org/10.1145/3079452.3079461

DH '17, July 2-5, 2017, London, United Kingdom

© 2017 Association for Computing Machinery.

ACM ISBN 978-1-4503-5249-9/17/07...\$15.00. https://doi.org/10.1145/3079452.3079461 **1 INTRODUCTION**

Breast Cancer (BC) is the most common cancer and also the leading cause of cancer mortality in women worldwide. BC accounts for about 20-25% of all cancer types in women [21].

Finding algorithms to predict the growth of tumors has piqued the interest of researchers ever since the early days of cancer research. Many studies were carried out as an attempt to obtain reliable data on the natural history of BC growth.

Mathematical modeling can play a very important role in the prognosis of BC. Various mathematical models were built to describe primary tumor (PT) growth and distant metastases (MTS) growth separately [19].

These days, an exponential, Gompertz, logistic and von Bertalanffy models are included in a group of classical mathematical models of PT growth [1]. For the breast data, the observed linear dynamics were best captured by an exponential model, which is situated for the description of PT growth and, also, for secondary distant MTS growth [7, 8, 10–16, 18]. As for Gompertz and logistic models, they are used rarely in order to describe PT growth or secondary distant MTS growth [5, 9, 17, 25].

The duration of the period from the first BC cell to death refers to the natural history of BC [2]. Secondary distant MTS appear in various time in different organs. The interval between removal of PT and the first clinical manifestation of MTS (MTS free survival time or non-visible period) determined by PT size, the number of affected lymph nodes and MTS growth rate [3, 5, 7–10, 12–16, 18, 22, 25, 26]. Survival (lifetime) is the period between the date of diagnosis (TNM staging system of BC) and the date of a patient death [21]. Survival among BC patients (%) indicates the percentage of people in a study or treatment group who are alive for a given period of time after diagnosis. The percentage of patients who live at least 5-, 10-, 15-, 20-, 25- and 30-years after being treated PT is defined as 5-, 10-, 15-, 20-, 25- and 30-years observed survival rate of BC patients [9, 21].

It is important to highlight that the natural history of BC continues after removal of PT. The next stage begins with secondary distant MTS manifestation. When the MTS reach the threshold volume, patients die from progression of BC [1, 4, 7–10, 12–16, 18, 20, 22]. All BC patients get a comprehensive treatment of PT, so the *whole natural history of BC* should include the period of secondary distant MTS growth (Fig. 1):

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

- 1) the **non-visible** period of PT growth;
- the visible period of PT growth, diagnostics and removal of PT;
- 3) the non-visible period of secondary distant MTS growth;4) the visible period of secondary distant MTS growth, diagnostics, treatment and patient's death.

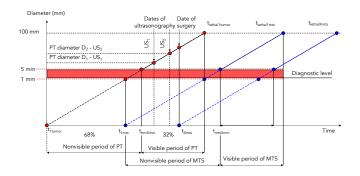


Figure 1: Scheme of the *whole natural history* **of BC (stage I-II)[4, 7, 12, 14, 20, 22].** As it should be highlighted, the main feature is that model describes PT growth and secondary distant MTS growth as a whole (as indivisible dependent process). Ordinate (Y): Diameter of tumor (mm). Abscissa (X): Time (years).

| Legend of Fig. | 1: | |
|---------------------------|-------|---------------------------------------------|
| t _{1tmr} | _ | date of appearance of the first BC stem |
| | | cell; |
| $t_{1tmr5mm}$ | _ | date of appearance of the visible PT with |
| | | size 5 mm; |
| t _{lethal1tumor} | _ | date of appearance of the lethal PT with |
| | | size 100 mm (when PT reaches the thresh- |
| | | old volume); |
| t_{1mts} | _ | date of appearance of the first MTS stem |
| | | cell, which coincides with the period of |
| | | 20 th doubling time; |
| $t_{1mts5mm}$ | _ | date of appearance the first visible MTS of |
| | | breast cancer with size 5 mm; |
| t _{lethal1mts} | _ | date of appearance the first lethal MTS of |
| | | BC with size 100 mm (when secondary dis- |
| | | tant MTS reaches the threshold volume); |
| t_{Xmts} | _ | date of appearance nXmts cell of BC MTS, |
| | | which coincides with date of surgery; |
| $t_{Xmts5mm}$ | — | date of appearance nXmts visible BC MTS |
| | | with size 5 mm; |
| t _{lethalXmts} | — | date of appearance nXmts lethal BC MTS |
| | | with size 100 mm; |
| US_1 | _ | date and sizes of the first US of PT; |
| US_2 | _ | date and sizes of the second US of PT. |
| Given the rela | ation | between PT and MTS the problem of dis- |

Given the relation between PT and MTS, the problem of discovering BC process seems to be twofold: firstly, it is important to describe the *whole natural history of BC* to understand the process as a whole; secondly, it is necessary to predict the period of a clinical MTS manifestation. Yet, the papers available for this do not offer mathematical growth models of MTS that relate to TNM classification. That leads to the demand building a mathematical model that rests on an exponential classical mathematical model and describes *whole natural history of BC* and corresponds to TNM classification. Moreover, the latter aspect of the problem is reflected only by statistical tools that are available as open source. In other words, a patient provides diagnostic data to predictor, and the tool calculates MTS free period and survival according to statistical data. Consequently, it is necessary to create a predictor that makes prognosis of BC for a patient independently from statistical data, and requires no expensive diagnostic data. Thus, this research possesses a novelty since it is the first time the following tools for BC have been proposed: a) *whole natural history of BC*; b) mathematical growth model corresponding to TNM; c) non statistical software tool for prediction of BC developing.

To avoid terminological ambiguities, we dwell upon recalling some standard terms and TNM staging system of BC (Table 1) [21].

Table 1: TNM staging system

| - | | | |
|-------------------|----------------|-------------|-------------|
| Stage Parameter T | | Parameter N | Parameter M |
| I | T1 | N0 | M0 |
| II | T1, T2 | N0, N1 | M0 |
| III | T1, T2, T3, T4 | N1, N2, N3 | M0 |
| IV | any T | any N | M1 |

Legend of Table 1:

| parameter T | _ | size of PT: T1 = 0.1 d \leq 2 cm; T2 = 2 d \leq 5 |
|-------------|---|-------------------------------------------------------|
| | | cm; $T3 = d > 5$ cm; $T4 = spread$; |
| parameter N | _ | the number of affected lymph nodes: N0: n |
| | | = 0; N1: n = 1-3; N2: n = 4-9; N3: n = 10-18; |
| parameter M | _ | existence of distant MTS (lungs, bones, |
| | | liver, etc): M0 = MTS not exist; M1 = MTS |
| | | exist. |

The **goal** of the research is to improve the prediction accuracy of BC process using the original **Co***nsolidated mathematical growth* **M***odel of primary tumor and secondary MTS of patients with lymph nodes MTS* (CoM-III). To make precise the scope of the study it is necessary to fulfil several **tasks**:

- modelling the *whole natural history* of PT and MTS for stage III;
- (2) developing the adequate and precise CoM-III that reflects relations between PT and secondary MTS of patients with lymph nodes MTS;
- (3) analysing the CoM-III scope of applications;
- (4) implementing the model as a software tool.

Practical value. As it turns out, a new software tool for prediction of BC developing can calculate more accurately: a) MTS free period; b) survival for stage III of BC including PT and secondary MTS of patients with lymph nodes MTS. Moreover, the predictor can estimate a quality of treatment which was prescribed to a patient. Summarising: the CoM-III describes correctly PT and secondary distant MTS growth of T1N1M0, T2N1M0, T1-2N2M0, T3N1-2M0, T4N1-2M0, T1-4N3M0 [T1-4N1-3M0] stages in patients with lymph nodes MTS (N1-3).

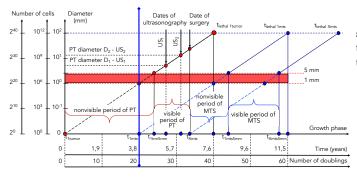
2 MATERIALS AND METHODS

Consolidated mathematical growth model of PT and secondary MTS, I-II stages (CoMPaS)

In 2015 we proposed a consolidated mathematical growth model of PT and secondary MTS (CoMPaS) that describes correctly PT growth (parameter T) as well as secondary MTS growth (parameter M), corresponds to TMN [23]. Also, the CoMPaS might facilitate the survival (lifetime) and, as a consequence, make predictions of a future metastatic manifestation after removal of PT.

It is important to define several admissions, where rows 1-3 rests on [1, 7, 8, 10-15, 18, 20, 22, 24]:

- an exponential growth model is used widely for description *natural* growth rate of the primary BC;
- the *natural* rate of secondary distant MTS is the same as *natural* growth rate of the primary BC;
- the period of appearance of the first metastatic cell of secondary distant MTS coincides with the 20th doubling of the primary BC. It allows us to define the **non-visible** growth period of MTS and the initial period of **non-visible** MTS manifestation;
- 4) the whole nature history of the PT and secondary distant



| Legend of Fig. 2: | |
|---------------------------|-------------------------------------------------------|
| red points | correspond to PT growth; |
| blue points | correspond to distant MTS growth; |
| the non-visible period | of MTS growth starts with a removal of |
| | PT; |
| red horizontal block | indicates a minimal size of tumor that can |
| | be diagnosed [1mm; 5mm]; |
| growth rate | is equal as for PT as for MTS (CoMPaS for |
| | Stages I-II); |
| three vertical lines | on the left side of the Fig. 2 show the num- |
| | ber of cells in tumor with corresponding |
| | diameter; |
| 60 th doubling | means the death of a patient; |
| \xrightarrow{time} | illustrates a mean survival at corresponded doubling. |

The CoMPaS rests on an exponential growth model and consisted of nonlinear and linear determined equations [1, 3, 5, 7, 8, 10–16, 18, 20, 22, 24, 26]:

$$\begin{cases} \frac{dV}{dt} = \frac{\log 2}{DT} V, \quad t \leq DT \ \log_2\left(\frac{\theta \ DT}{\log 2} \ V_0\right); \\ \frac{dV}{dt} = \theta \log V, \quad t > DT \ \log_2\left(\frac{\theta \ DT}{\log 2} \ V_0\right); \\ V(t=0) = V_0 \\ Survival = PT_{\log(V)} + Nonvis_{log} + Vis_{log} = 60; \\ TVDT_{non} = TVDT_{vis} = \frac{NonVis_{days} + Vis_{days}}{NonVis_{log} + Vis_{log}}; \end{cases}$$

| $\frac{\log 2}{DT}$ | _ | the fraction of proliferative cells times; | | | | |
|---------------------|---|------------------------------------------------|--|--|--|--|
| θ | _ | drives the linear phase; | | | | |
| $pT_{\log(V)}$ | — | the number of PT doublings; | | | | |
| Nonvislog | _ | the number of doublings for non-visible | | | | |
| | | growth period of MTS; | | | | |
| Vis _{log} | _ | the number of doublings for visible | | | | |
| 9 | | growth period of MTS; | | | | |
| TVDT | _ | tumor volume doubling time; | | | | |
| 60 doublings | _ | the whole nature growth history of the PT | | | | |
| | | and secondary distant MTS. | | | | |

According to M. Schwartz (1961): "the doubling time (*DT*), representing the time for 1 cell (or of the tumor as a whole if each cell has the same doubling time) to double in volume, and it is equivalent to the interval between successive mitoses" [20]:

$$DT = \frac{\log 2 (t_1 - t_0)}{\log V_1 - \log V_0},$$

- the period of doubling time;
- tumor volume at time *t* of the pre-surgery measurement;
- tumor volume at time of the first measurement;
- $t_1 t_0$ the period between the first and presurgery measurements (days).

3 RESULTS

DT

 V_1

 V_0

Consolidated mathematical growth model of PT and secondary MTS of patients with lymph nodes MTS, III stage (CoM-III)

Stage III (T1-4N1-3M0) means that lymph nodes MTS (N1-3) exist meanwhile PT (T1-4) is growing [6, 21]. Moreover, patients with lymph nodes MTS have lower survival comparing with patients without lymph nodes MTS. Unfortunately, the papers available for this do not offer mathematical growth models of stage III of BC that cover growth process of PT and secondary MTS in patients with lymph nodes MTS.

We propose a new mathematical growth model for PT and secondary MTS in patients with lymph nodes MTS. The model may help to improve predicting accuracy of BC process using an original mathematical model referred to CoM-III and corresponding software. Consequently, we are interested in:

- 1) modelling the *whole natural history* of PT and secondary MTS in patients with lymph nodes MTS;
- developing adequate and precise CoM-III that reflects relations between PT and MTS;
- analysing the CoM-III scope of application; 4) implementing the model as a software tool.

The period of appearance of the first metastatic cell coincides with 20th doubling of PT. At stage III the period of MTS manifestation depends on the number of lymph nodes MTS.

The CoM-III rests upon CoMPaS, and by complementing formulas::

$$\begin{cases} sMts_{\log(V)(N+)} = pT_{\log(V)} - 20; \\ K_{sMts(N+)} = \frac{20}{sMts_{\log(V)(N+)} \times 18 \times n} + 1; \\ TVDT_{sMts(N+)} = \frac{TVDT_{pT}}{K_{sMts(N+)}}; \end{cases}$$

 $sMts_{\log(V)(N+)}$ the number of doublings of secondary MTS in patients with lymph nodes MTS; $pT_{\log(V)}$ the number of doublings of PT; the number of doublings of PT that co-20 incides with the appearance of the first metastatic cell; correcting coefficient of secondary MTS of $K_{sMts(N+)}$ patients with lymph nodes MTS relating with PT growth rate; the number of affected lymph nodes (min п $= 0, \max = 18$); $TVDT_{sMts(N+)}$ tumor volume doubling time of secondary MTS of patients with lymph nodes MTS

It allows us to calculate different growth periods of PT and secondary MTS of patients with lymph nodes MTS:

of the PT $(TVDT_{pT})$.

- 1) **non-visible** period for PT;
- non-visible period for secondary MTS of patients with lymph nodes MTS;

relating with tumor volume doubling time

3) **visible** period for secondary MTS of patients with lymph nodes MTS.

Predictor CoM-III

At this stage, it is relevant to shed light on predictor specifications. We implement the CoM-III as a software tool. The application is build using Swift and referred as CoMPaS. The CoMPaS is available for iOS devices (iOS 9+).

INPUT DATA:

- the first ultrasound diagnostic data:
 - date
 - diameter (mm)
- the second ultrasound diagnostic data:
 - date
 - diameter (mm)
- the number of affected lymph nodes (n)

OUTPUT DATA:

- forecast:
 - the number of months
 - category of forecast:
 - favorable
 - * mid-favorable
 - * unfavorable

To flesh this out, the Fig.3 provides a clinical example for a patient with seven affected lymph nodes.

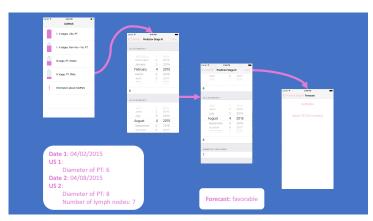


Figure 3: Clinical example

Under such circumstances, it is necessary to collect predictions in one database to compare forecasts with real data and estimate effectiveness of proposed model. Consequently, the CoMPaS connects to database that allows us to test application and model.

As it turns out, the new predictive tool: 1) is a solid foundation to develop future studies of BC models; 2) does not require any expensive diagnostic tests; 3) is the first predictor that makes forecast using only current patient data, whilst the others are based on the additional statistical data.

Calculations of *whole natural history* **resting on CoM-III**

Given all above, it is relevant to dwell upon building the *whole natural history* of BC stage III. Provided formulas allow calculating:

- the number of doublings for secondary MTS relying only on two measurements of PT sizes;
- the correcting coefficient of secondary MTS spreading rate in patients with lymph nodes MTS relating with PT growth rate;
- doubling time of secondary MTS.

Data of a mean diameter of PT for each stage (T1, T2, T3, T4) is obtained from table 1 of paper J. Engel et al. [6]. The number of affected lymph nodes corresponds to TNM staging system of BC [21]. The variety of doubling time of PT (T1, T2, T3, T4) relying on PT sizes is calculated from fig 6 of paper D. Holzel et al. [9]. Table 2 shows results of calculations via CoM-III.

| | | T1a (mm) 1 < d ≤ 5 | $\begin{array}{l} T1b \ (mm) \\ 5 < d \leq 10 \end{array}$ | $\begin{array}{l} T1c \ (mm) \\ 10 < d \leq 20 \end{array}$ | $\begin{array}{l} T2 \ (mm) \\ 20 < d \leq 50 \end{array}$ | T3-4 (mm) d > 50 | |
|----|------------------------------------------|-----------------------|------------------------------------------------------------|-------------------------------------------------------------|------------------------------------------------------------|---------------------|------|
| 1 | Mean size of PT at surgery | 4.5 | 8.5 | 15.1 | 28.5 | 64.6 | [6] |
| 2 | pT_{log} | 26.4 | 29.2 | 31.7 | 34.4 | 38.0 | |
| 3 | TVDT _{pT} | 80.0 | 75.0 | 70.0 | 65.0 | 60.0 | [9] |
| 4 | Mean $K_{sMts(N-)}$ (N0, n=0) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | |
| 5 | $TVDT_{sMts(N-)}$ (N0, n=0) | 80.0 | 75.0 | 70.0 | 65.0 | 60.0 | [23] |
| 6 | Mean $K_{sMts(N+)}$ (N1, $n_{mean}=2$) | 1.23 | 1.16 | 1.12 | 1.09 | 1.05 | |
| 7 | $TVDT_{sMts(N+)}$ (N1, $n_{mean}=2$) | 65.09 | 64.44 | 62.37 | 59.77 | 56.90 | [23] |
| 8 | Mean $K_{sMts(N+)}$ (N2, $n_{mean}=6$) | 1.69 | 1.49 | 1.37 | 1.26 | 1.16 | |
| 9 | $TVDT_{sMts(N+)}$ (N2, $n_{mean}=6$) | 47.42 | 50.28 | 51.21 | 51.48 | 51.56 | [23] |
| 10 | Mean $K_{sMts(N+)}$ (N3, n_{mean} =14) | 2.60 | 2.15 | 1.86 | 1.61 | 1.38 | |
| 11 | $TVDT_{sMts(N+)}$ (N3, n_{mean} =14) | 30.74 | 34.93 | 37.71 | 40.30 | 43.42 | [23] |

Table 2: T1-3N0-3M0

Legend of Table 2:

- TNM parameters depend on PT size: T1, T2, T3, T4, N1, N2, N3, M0 [21] (see detailed description on Fig. 5 - Fig. 9);
- row 1 uses data of the mean sizes of PT at surgery from tables of paper [6];
- row 2 is calculated from row 1;
- row 3 uses data from figure of paper [9];
- *n_{mean}* is the mean number of lymph nodes whereas:
 - N1 means that the number of lymph nodes can equal any integer number from compact [1; 3];
 - N2 means that the number of lymph nodes can equal any integer number from compact [4; 9];
 - N3 means that the number of lymph nodes can equal any integer number from compact [10; 18];
 - N1-3 means that the number of lymph nodes can equal any integer number from compact [1; 18].
- $K_{sMts(N-)}$ means no MTS in lymph nodes (N0, $n_{mean}=0$);
- the variety of $K_{sMts(N+)}$ is calculated for N1-3;
- the variety of $TVDT_{sMts(N+)}$ is calculated for N1-3.

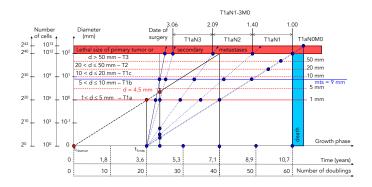


Figure 4: T1aN0-3M0. Whole natural history of PT and secondary MTS of patients with lymph nodes MTS according to CoM-III. Parameter T (T1a: 1mm < d \leq 5mm) - diameter of PT. Parameter N (N0: n=0; N1: n=1-3; N2: n=4-9, N3: n=10-18) - affected lymph nodes.

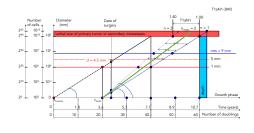
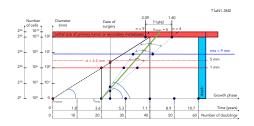


Figure 5





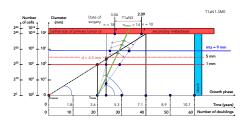


Figure 7

Legend of Fig. 5-7:

| Legend of Fig. 5 7. | | | |
|---------------------|--------------------------------------------------------------------------------------------------------|--|--|
| red points | correspond to PT growth; | | |
| blue points | correspond to distant MTS growth; | | |
| lines | define boundaries of correcting coeffi- | | |
| green line | cients values for patients with N1, N2, N3; corresponds to the mean number of lymph nodes n_{mean} . | | |

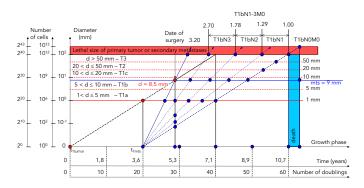


Figure 8: T1bN0-3M0. Whole natural history of PT and secondary MTS of patients with lymph nodes MTS according to CoM-III. Parameter T (T1b: 5mm < d \leq 10mm) - diameter of PT. Parameter N (N0: n=0; N1: n=1-3; N2: n=4-9, N3: n=10-18) - affected lymph nodes.

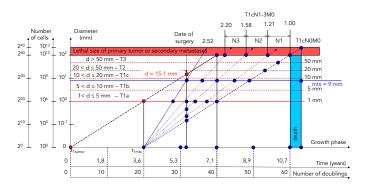


Figure 9: T1cN0-3M0. Whole natural history of PT and secondary MTS of patients with lymph nodes MTS according to CoM-III. Parameter T (T1c: 10mm < d \leq 20mm) - diameter of PT. Parameter N (N0: n=0; N1: n=1-3; N2: n=4-9, N3: n=10-18) - affected lymph nodes.

4 CONCLUSION

The CoM-III model and predictive software: a) detect different growth periods of PT and secondary distant MTS growth in patients with lymph nodes MTS; b) make forecast of the period of secondary distant MTS appearance in patients with lymph nodes MTS; c) have higher average prediction accuracy than the other tools; d) can improve forecasts on survival of BC and facilitate optimisation of diagnostic tests. The following are calculated by CoM-III: the number of doublings for non-visible and visible growth periods of secondary distant MTS; tumor volume doubling time (days) for **non-visible** and **visible** growth periods of secondary distant MTS. The original CoM-III enables us, for the first time, to predict the whole natural history of PT and secondary distant MTS growth on each stage (T1, T2, T3, T4) for patients with/without lymph nodes MTS relying only on PT sizes. Summarising: CoM-III a) describes correctly PT and secondary distant MTS growth of T1N1M0, T2N1M0, T1-2N2M0, T3N1-2M0, T4N1-2M0, T1-4N3M0 [T1-4N1-3M0] stages in patients with lymph nodes MTS (N1-3); b) facilitates

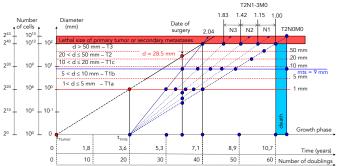


Figure 10: T2N0-3M0. Whole natural history of PT and secondary MTS of patients with lymph nodes MTS according to CoM-III. Parameter T (T2: $20mm < d \le 50mm$) - diameter of PT. Parameter N (N0: n=0; N1: n=1-3; N2: n=4-9, N3: n=10-18) - affected lymph nodes.

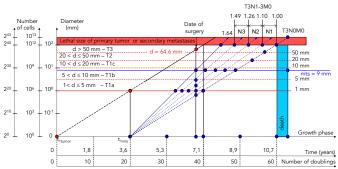


Figure 11: T3N0-3M0. Whole natural history of PT and secondary MTS of patients with lymph nodes MTS according to CoM-III. Parameter T (T3: d > 50mm) - diameter of PT. Parameter N (N0: n=0; N1: n=1-3; N2: n=4-9, N3: n=10-18) - affected lymph nodes.

the understanding of the appearance period and inception of secondary distant MTS.

Work still to be done: 1. To test the CoM-III on clinical data. 2. To analyse forecasts statistically. 3. To implement CoM-III to medical practice.

REFERENCES

- S. Benzekry, C. Lamont, A. Beheshti, J.M. Tracz, A.and Ebos, L. Hlatky, and P. Hahnfeldt. 2014. Classical mathematical models for description and prediction of experimental tumor growth. *PLoS Comput Biol* 10, 8 (aug 2014). DOI: https: //doi.org/10.1371/journal.pcbi.1003800
- [2] H.J. Bloom, W.W. Richarson, and E.J. Harries. 1962. Natural history of untreated breast cancer (1805-1933). Comparison of untreated and treated cases according to histological grade of malignancy. *Br Med J* 2, 5299 (1962), 213–221. https: //www.ncbi.nlm.nih.gov/pubmed/13870135
- [3] S.E. Clare, F. Nakhlis, and J.C. Panetta. 2000. Molecular biology of breast cancer metastasis. The use of mathematical models to determine relapse and to predict response to chemotherapy in breast cancer. *Breast Cancer Res* 2, 6 (2000), 430–435. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC138666/
- [4] V.P. Collins, R.K. Loeffler, and H. Tivey. 1956. Observations on growth rates of human tumors. Am J Roentgen 76, 5 (1956), 988–1000. https://www.ncbi.nlm.nih. gov/pmc/articles/PMC2008056/

- [5] F.A. Coumans, S. Siesling, and L.W. Terstappen. 2013. Detection of cancer before distant metastasis. *BMC Cancer* 13, 283 (jun 2013), 1–12. DOI: https://doi.org/10. 1186/1471-2407-13-283
- [6] J. Engel, R.T. Emeny, and D. Holzel. 2012. Positive lymph nodes do not metastasise. *Cancer Metastasis Rev* 31, 1-2 (2012), 235–246. DOI: https://doi.org/10.1007/ s10555-011-9343-7
- [7] S. Friberg. 2005. On the growth rates of human malignant tumors: implications for medical decision making. *J Oncol* 55, 1 (aug 2005), 1–22. DOI: https://doi.org/ 10.1002/(SICI)1096-9098(199708)65
- P.M. Gullino. 1977. Natural history of breast cancer. Progression from hyperplasia to neoplasia as predicted by angiogenesis. *Cancer* 39, 6 (jun 1977), 2697–2703. DOI: https://doi.org/10.1002/1097-0142(197706)39
- [9] D. Holzel, R. Eckel, R.T. Emeny, and J. Engel. 2010. Distant metastases do not metastasise. *Cancer Metastasis Rev* 29, 4 (sep 2010), 737–750. DOI:https://doi. org/10.1007/s10555-010-9260-1
- [10] S. Koscielny, M.G. Le, and M. Tubiana. 1989. The natural history of human breast cancer. The relationship between involvement of axillary lymph nodes and the initiation of distant metastases. *Br J Cancer* 59, 5 (may 1989), 775–782. https://www.ncbi.nlm.nih.gov/pubmed/2736212
- [11] S. Koscielny, M. Tubiana, and M.G. Le. 1984. Breast cancer: relationship between the size of the primary tumour and the probability of metastatic dissemination. *Br J Cancer* 49, 6 (jun 1984), 709–715. https://www.ncbi.nlm.nih.gov/pubmed/ 6733019
- [12] S. Koscielny, M. Tubiana, and A.-J. Valleron. 1985. A simulation model of the natural history of human breast cancer. *Br J Cancer* 52, 4 (oct 1985), 515–524. https://www.ncbi.nlm.nih.gov/pubmed/4063132
- [13] Y.T. Lee and J.S.Jr. Spratt. 1972. Rate of growth of soft tissue metastases of breast cancer. *Cancer* 29, 2 (feb 1972), 344–348. DOI: https://doi.org/10.1002/ 1097-0142(197202)29
- [14] R.S. Lin and S.K. Plevritis. 2012. Comparing the benefits of screening for breast cancer and lung cancer using a novel natural history model. *Cancer Causes Control* 23, 1 (jan 2012), 175–185. DOI:https://doi.org/10.1007/s10552-011-9866-9
- [15] V.M. Moiseenko. 2002. Natural history of breast cancer. Practical oncology 1 (2002), 6–14. http://www.practical-oncology.ru/arh009/02.pdf

- [16] R. Molina-Pena and M.M. Alvarez. 2012. A simple mathematical model based on the cancer stem cell hypothesis suggests kinetic commonalities in solid tumor growth. *PLoS One* 7, 2 (feb 2012), 175–185. DOI: https://doi.org/10.1126/science. 1065467
- [17] L. Norton. 1988. A Gompertzian model of human breast cancer growth. Cancer Res 48, 24 (1988), 7067–7071. DOI: https://doi.org/10.1126/science.1065467
- [18] A.W. Pearlman. 1976. Breast cancer: Influence of growth rate on prognosis and treatment evaluation. *Cancer* 38, 4 (1976), 1826–1833. https://www.ncbi.nlm.nih. gov/pubmed/991096
- [19] I.A. Rodriguez-Brenes, N.L. Komarova, and D. Wodarz. 2013. Tumor growth dynamics: insights into evolutionary processes. *Cancer* 28, 10 (oct 2013). DOI: https://doi.org/10.1126/science.1065467
- [20] M. Schwartz. 1961. A biomathematical approach to clinical tumour growth. Cancer 14 (nov 1961), 1272–1294. DOI: https://doi.org/10.1002/1097-0142(196111/ 12)14
- [21] R. Shah, K. Rosso, and S.D. Nathanson. 2014. Pathogenesis, prevention, diagnosis and treatment of breast cancer. World J Clin Oncol 5, 3 (aug 2014), 283–298. https://www.ncbi.nlm.nih.gov/pubmed/25114845
- [22] M. Tubiana and A. Courdi. 1989. Cell proliferation kinetics in human solid tumors: relation to probability of metastatic dissemination and long-term survival. *Radiother Oncol* 15, 1 (1989), 1–18. https://www.ncbi.nlm.nih.gov/pubmed/2664909
- [23] Ella Turumina and Alexey Neznanov. 2015. Consolidated mathematical growth model of breast cancer. In School and Conference of the Kharkevich Institute for Information Transmission Problems Information Technologies and Systems. IITP RAS, http://itas2015.iitp.ru/pdf/1570162553.pdf arXiv:http://itas2015.iitp.ru/pdf/1570162553.pdf
- [24] L. von Bertalanffy. 1957. Quantitative laws in metabolism and growth. Q Rev Biol 32, 3 (1957), 217–231. https://www.ncbi.nlm.nih.gov/pubmed/13485376
- [25] H. Weedon-Fekjaer, B.H. Lindqvist, L.J. Vatten, O.O. Aalen, and S. Tretli. 2008. Breast cancer tumor growth estimated through mammography screening data. *Breast Cancer Rev* 10, 3 (2008), 1–13. DOI:https://doi.org/10.1186/bcr2092
- [26] H.R. Withers and S.P. Lee. 2006. Modeling growth kinetics and statistical distribution of oligometastases. *Semin Radiat Oncol* 16, 2 (2006), 111–119. DOI: https://doi.org/10.1016/j.semradonc.2005.12.006