Perturbation theory of non-demolition measurements

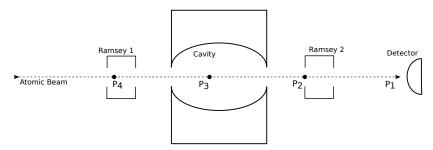
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Atlanta, October 2016

 M Ballesteros, MF, J Fröhlich and B Schubnel: "Indirect acquisition of information in quantum mechanics." JSP 162 (2016)

 M Ballesteros, N Crawford, MF, J Fröhlich and B Schubnel: "Perturbation theory of non-demolition measurements." in preparation

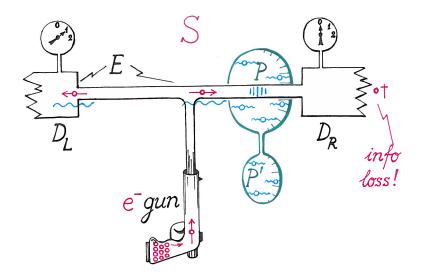
Haroche's experiment



Phenomena: After a long sequence of measurement results ξ_1, ξ_2, \ldots the state of light in the cavity is close to a photon number state.

[Haroche et. al. Nature 2007, Siddiqi et. al. Nature 2013]

Electron gun



Mathematical Description

Jump operators $V_{\xi}, \xi \in \sigma$, with a normalization $\sum_{\xi \in \sigma} V_{\xi}^* V_{\xi} = 1$. Probability to measure ξ is $\text{Tr}(V_{\xi}^* V_{\xi} \rho)$ and the state changes as

$$ho
ightarrow rac{V_{\xi}
ho V_{\xi}^*}{\operatorname{Tr}(V_{\xi}
ho V_{\xi}^*)}.$$

For an infinity history $\underline{\xi} = \xi_1, \xi_2, \dots$ we put $V^{(n)}(\underline{\xi}) = V_{\xi_1} \dots V_{\xi_n}$, the probability of a finite history ξ_1, \dots, ξ_n is then

$$\mathbb{P}_{\rho}(\xi_1,\ldots,\xi_n) = \operatorname{Tr}((V^{(n)}(\underline{\xi}))^* V^{(n)}(\underline{\xi})\rho)$$

and the state evolves to

$$\rho_n(\underline{\xi}) = \frac{V^{(n)}(\underline{\xi})\rho(V^{(n)}(\underline{\xi}))^*}{\operatorname{Tr}(V^{(n)}(\underline{\xi})\rho(V^{(n)}(\underline{\xi}))^*)}.$$

Remarks

 Products of i.i.d. random matrices studied by [Furstenberg, Kesten Annals of Stat. 1960] and many others with applications to 1D random Schrödinger e.g [Bougerol, Lacroix (1985)]
 Measurement in Quantum Mechanics also leads to study of

Measurement in Quantum Mechanics also leads to study of product of matrices but with non i.i.d. measure.

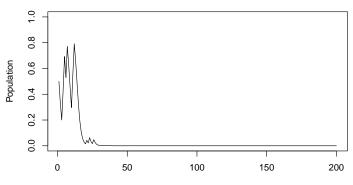
2. The setting is an example of a finitely correlated state [Fannes, Nachtergaele, and Werner CMP 144].

Example $\varepsilon = 0$

For a two level system and $\sigma = \{e, g\}$ we put

$$V_e = e^{-iarepsilon\sigma_1} \left(egin{array}{cc} \sqrt{p} & 0 \ 0 & \sqrt{q} \end{array}
ight), \quad V_g = e^{-iarepsilon\sigma_1} \left(egin{array}{cc} \sqrt{1-p} & 0 \ 0 & \sqrt{1-q} \end{array}
ight)$$

For $\varepsilon = 0$ the population of $\mathcal{N} = \sigma_z$ approaches an eigenstate,



Population Tracking

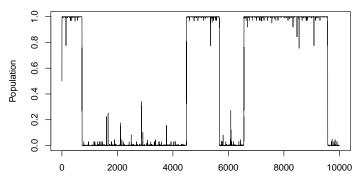
Time Step

Example $\varepsilon \neq 0$

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For $\varepsilon \neq 0$ the population of $\mathcal{N} = \sigma_z$ jumps between eigenstates,



Population Tracking

Time Step

Non-demolition case and its perturbations

For an observable \mathcal{N} and a Hamiltonian H with $[H, \mathcal{N}] \neq 0$ we put

$$V_{\xi}^{(arepsilon)}=e^{-iarepsilon H}V_{\xi}(\mathcal{N})$$

for some complex functions $V_{\xi}(\cdot)$. In the case $\varepsilon = 0$ we have $[V_{\xi}, V_{\xi'}] = 0$ and

$$\mathbb{P}_{\rho}(\xi_1,\ldots,\xi_n) = \int_{\sigma(\mathcal{N})} |V_{\xi_1}(\nu)|^2 \ldots |V_{\xi_n}(\nu)|^2 \mathrm{d}\lambda_{\rho}(\nu),$$

where λ_ρ is a spectral measure of $\mathcal{N}.$ Interpreting ν as an unknown we define maximum likelihood estimate

$$\hat{\mathcal{N}}_k(\underline{\xi}) = \operatorname{argmax}_{\nu \in \sigma(\mathcal{N})} l_k(\nu | \underline{\xi}), \quad l_k(\nu | \underline{\xi}) := \frac{1}{k} \sum_{j=1}^k \log |V_{\xi_j}(\nu)|^2.$$

Non-Demolition Case, $\varepsilon = 0$

For set $N \in \sigma(\mathcal{N})$ let let $\Pi(N)$ be the associated spectral projection and $S(\nu|N) = \inf_{\nu' \in N} \sum_{\xi \in \sigma} |V_{\xi}(\nu)|^2 [I(\nu|\xi) - I(\nu'|\xi)].$

Theorem (Law of Large Numbers)

Suppose $\nu \to V_{\xi}(\nu)$ is injective and $V_{\xi}(\cdot)$ is continuos for all $\xi \in \sigma$, then the maximum likelihood estimator $\hat{\mathcal{N}}_k$ converges almost surely to a random variable $\hat{\mathcal{N}}_{\infty}$. For any Borel set $N \subset \sigma(\mathcal{N})$,

$$\mathbb{P}_{\rho}(\underline{\xi}: \lim_{k \to \infty} \hat{\mathcal{N}}_k \in N) = \operatorname{Tr}(\Pi(N)\rho).$$

Moreover if N is a closed subset of $\sigma(N)$ contained in the support of the measure λ_{ρ} then we have

$$-\lim_{k o\infty}rac{1}{k}\log\mathrm{Tr}(\Pi(N)
ho_k)=S(\hat{\mathcal{N}}_\infty|N),\quad \mathbb{P}_
ho-almost\ surely.$$

Non-Demolition Case - references

When spectrum of $\ensuremath{\mathcal{N}}$ is discrete the Law of Large Numbers was proved in

- Maassen, Kümmerer 2006
- Bauer, Bernard PRA 2011
- Mabuchi et. al. IEEE 2004

The large deviation theory

Bauer, Benoist, Bernard AHP 2013

Demolition Case

We make measurement times t_1, t_2, \ldots of ξ_1, ξ_2, \ldots random and distributed by Poisson distribution N_t , then the evolution is

$$\tau_{\varepsilon}^{(s)}(\underline{t},\underline{\xi})\rho = e^{-i\varepsilon H(s-t_{N_s})}V_{\xi_{N_s}}\dots e^{-i\varepsilon Ht_1}\rho e^{i\varepsilon Ht_1}V_{\xi_1}\dots e^{i\varepsilon H(s-t_{N_s})}.$$

This is an unravelling of Lindblad evolution,

$$\mathbb{E}[au_arepsilon^{(m{s})}] = exp(m{s}\mathcal{L}_arepsilon), \quad \mathcal{L}_arepsilon
ho = -iarepsilon[H,
ho] + \sum_{\xi\in\sigma}V_\xi
ho V_\xi^* -
ho.$$

For a sampling time T > 0 we define

$$\hat{\mathcal{N}}_{s} := \operatorname{argmax}_{\nu \in \sigma(\mathcal{N})} \frac{1}{N_{s+T} - N_{s}} \sum_{j=N_{s}}^{N_{s+T}} I(\nu | \xi_{j}).$$

To avoid dealing with overlapping data we set $\mathcal{M}_{jT} = \hat{\mathcal{N}}_{jT}$, for $j \in \mathbb{N}$ and extend the definition of \mathcal{M}_t to all $t \ge 0$ by declaring it to be piecewise constant on the intervals [jT, (j+1)T).

Demolition Case

Let
$$\mathcal{N} = \sum_{\nu} \nu P_{\nu}$$
 and define
$$\mathcal{P}\rho = \sum_{\nu \in \sigma(\mathcal{N})} P_{\nu}\rho P_{\nu}, \quad P_{\nu} = |\nu\rangle \langle \nu|.$$

We define an operator Q on the range of \mathcal{P} by

$$\varepsilon^2 Q = -\mathcal{P}\mathcal{L}_{\varepsilon}\mathcal{P}_{\perp}\mathcal{L}_0^{-1}\mathcal{P}_{\perp}\mathcal{L}_{\varepsilon}\mathcal{P}.$$

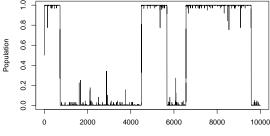
The matrix Q defines a Markov Kernel on $\sigma(\mathcal{N})$ with elements

$$\operatorname{Tr}(P_{\nu'}QP_{\nu}) = \begin{cases} \sum_{\beta \neq \nu} \frac{|\langle \beta | H | \nu \rangle|^2}{\sum_{\xi} V_{\xi}(\beta) \bar{V}_{\xi}(\nu) - 1} + c.c. & \text{for} \quad \nu = \nu' \\ -\frac{|\langle \nu' | H | \nu \rangle|^2}{\sum_{\xi} V_{\xi}(\nu') \bar{V}_{\xi}(\nu) - 1} + c.c. & \text{for} \quad \nu \neq \nu'. \end{cases}$$

Let Y_s be the continuous time Markov chain generated by Q started from an initial probability distribution $\pi_{\rho}(\nu) = \text{Tr}(P_{\nu}\rho)$.

Demolition Case

Theorem (Distribution of Jumps) Suppose $\nu \to V_{\xi}(\nu)$ is injective, and pick a positive I strictly smaller then $\min_{\nu,\nu'} S(\nu,\nu')$. Let $T = -\beta \log \varepsilon$, for some $\beta > \max\{2(1 - e^{-l})^{-1}, (1 - e^{-\frac{l}{2}})^{-1}\}$. Then under $\mathbb{P}_{\rho}^{(\varepsilon)}$, $\mathcal{M}_{\varepsilon^{-2}s}$ converges in law to Y_s , and the posterior density matrix $\rho_{\varepsilon^{-2s}}$ converges in law to P_{Y_s} .



Population Tracking



Thank you for your attention!