## Quantum Mechanics I

## Mathematical <br> Prerequisites II

## Linear Algebra Summary; Probability Theory

Tristan Hübsch

Department of Physics and Astronomy, Howard University, Washington DC http://phusics1.howard.edu/~thubsch/

## Mathematical Prerequisites II

## Linear Algebra Summary

Q $\mathbb{C}$-Linear vector space $V$ is a collection of objects $v_{i}$,
Q such that all $\mathbb{C}$-linear combinations $\Sigma_{i} \alpha_{i} v_{i}$ are also in $V$.
Q scalar product $(w, v)$ is a 2-argument function such that:
Qa: $(w, v)$ is a complex scalar
Q $b:(v, w)=(w, v)^{*}$
Qc: $\left(w, c_{1} v_{1}+c_{2} v_{2}\right)=c_{1}\left(w, v_{1}\right)+c_{2}\left(w, v_{2}\right)$
Qd: $(v, v) \geq 0$, and $(v, v)=0$ only if $v=0$
QTogether, $(b)$ and (c) imply $\left(c_{1} w_{1}+c_{2} w_{2}, v\right)=c_{1}{ }^{*}\left(w_{1}, v\right)+c_{2}{ }^{*}\left(w_{2}, v\right)$
QUsing $(d)$, we define the norm: $\|v\| \equiv(v, v)^{1 / 2}$
Linear functionals assigns to each vector a scalar $F[v] \in \mathbb{C}$
$Q$ Linearity: $F\left[c_{1} v_{1}+c_{2} v_{2}\right]=c_{1} F\left[v_{1}\right]+c_{2} F\left[v_{2}\right]$
$Q$ Vector space $V^{\circ}:\left(C_{1} F_{1}+C_{2} F_{2}\right)[\psi] \equiv C_{1} F_{1}[\psi]+C_{2} F_{2}[\psi]$
$Q$ Defined (also) by the scalar product: $W[\ldots]:=(w, \ldots)$

## Mathematical Prerequisites II

## Linear Algebra Summary

Q An operator acts on a vector and produces a vector
Q An operator is linear if $A\left(c_{1} \psi_{1}+c_{2} \psi_{2}\right)=\mathcal{c}_{1}\left(A \psi_{1}\right)+c_{2}\left(A \psi_{2}\right)$
Operator algebra
QSum: $(A+B) \psi=A \psi+B \psi$
Q Product: $A B \psi=A \circ B \psi=A(B \psi) ; A(B C)=(A B) C$ but $A B \neq B A$
$\bigcirc$ Commutator: $[A, B]:=A \circ B-B \circ A$
Q Adjoint: $\left(\chi, A^{+} \psi\right):=(\psi, A \chi)^{*}$ for all $\psi, \chi$
Q Just like the Hermitian conjugate of a matrix: $\left[M^{\dagger}\right]_{i j}=\left(M_{j i}\right)^{*}$
QSelf-adjoint: $\left(\chi, \boldsymbol{A}^{+} \psi\right)=(\chi, \boldsymbol{A} \psi)=(\psi, \boldsymbol{A} \chi)^{*}=\left(\psi, \boldsymbol{A}^{+} \chi\right)$
QJust like a Hermitiam matrix: $\left[M^{\dagger}\right]_{i j}=\left(M_{j i}\right)^{*}=M_{i j}$
Thm.1: If $(\psi, \boldsymbol{A} \psi)=(\psi, \boldsymbol{A} \psi)^{*}$, then $(\psi, \boldsymbol{A} \chi)=(\chi, \boldsymbol{A} \psi)^{*}$
Definition: If $\boldsymbol{A} \psi_{a}=a \psi_{a}$, then $a$ is an eigenvalue, $\psi_{a}$ the eigenfunction
Thm. 2 \& 3: If $\boldsymbol{A}^{+}=\boldsymbol{A}$, then all eigenvalues are real \& $\left(\psi_{a,} \psi_{b}\right)=0$ if $a \neq b$

## Mathematical Prerequisites II

## Linear Algebra Summary

QThm. $\pi: \quad A^{\dagger}=A \quad A|n\rangle=a_{n}|n\rangle, \quad\langle n \mid m\rangle=\delta_{n m} \quad \sum_{n}|n\rangle\langle n|=\mathbb{1}$

$$
A=\sum_{n} a_{n}|n\rangle\langle n| \quad f(\boldsymbol{A}):=\sum_{n} f\left(a_{n}\right)|n\rangle\langle n|
$$

QThm.4: If $A^{+}=A$, then there exist projection operators $E(\lambda)$, such that:

1. If $\lambda_{1}<\lambda_{2}$ then $E\left(\lambda_{1}\right) E\left(\lambda_{2}\right)=E\left(\lambda_{2}\right) E\left(\lambda_{1}\right)=E\left(\lambda_{1}\right)$.
2. If $\epsilon>0$ then $\lim _{\epsilon \rightarrow 0} E(\lambda+\epsilon)|\psi\rangle=E(\lambda)|\psi\rangle$.
3. $\lim _{\lambda \rightarrow-\infty} E(\lambda)|\psi\rangle=0$.
$E(\lambda)$ projects
4. $\lim _{\lambda \rightarrow+\infty} E(\lambda)|\psi\rangle=|\psi\rangle$.
5. $\int_{-\infty}^{+\infty} \mathrm{d} E(\lambda) \lambda=A$. - reconstructs $A$
onto states with eigenvalue $\leq \lambda$

Thm.5: If $A=A^{\dagger}, B=B^{\dagger}$, and $[A, B]=0$, then they have a complete set of common eigenvectors, $|a, b\rangle$
QThm.6: If $\left[A, B_{i}\right]=0,\left\{B_{i}\right\}$ a complete commuting set, $A=f\left(B_{i}\right)$

## Mathematical Prerequisites II

## Linear Algebra Summary

Q Note: $f(A):=\sum_{n} f\left(a_{n}\right)|n\rangle\langle n|,=\int_{-\infty}^{+\infty} \mathrm{d} E(\lambda) f(\lambda)$
QIf $A=A^{+}$has a purely discrete spectrum

$$
\begin{aligned}
& E(\lambda)=\sum_{n} \vartheta\left(\lambda-a_{n}\right)\left|a_{n}\right\rangle\left\langle a_{n}\right| \quad \mathrm{d} E(\lambda)=\sum_{n} \mathrm{~d} \lambda \delta\left(\lambda-a_{n}\right)\left|a_{n}\right\rangle\left\langle a_{n}\right| \\
& f(A)=\int_{-\infty}^{+\infty} \sum_{n} \mathrm{~d} \lambda \delta\left(\lambda-a_{n}\right) f(\lambda)\left|a_{n}\right\rangle\left\langle a_{n}\right|=\sum_{n} f\left(a_{n}\right)\left|a_{n}\right\rangle\left\langle a_{n}\right|
\end{aligned}
$$

For the continuous analogue, $Q \psi(x):=x \psi(x)$ for all $\psi(x)$
Then, $Q \psi_{\lambda}(x):=\lambda \psi_{\lambda}(x)$ implies that $\psi_{\lambda}(x)=\delta(\lambda-x)$
Q ...but $\delta(\lambda-x)$ is not square-normalizable, $\notin$ Hilbert space
Q $E(\lambda)=\vartheta(\lambda-x)$ and $\int_{-\infty}^{+\infty} \mathrm{d} E(\lambda) f(\lambda) \psi(x)=\int_{-\infty}^{+\infty} \mathrm{d}[\vartheta(\lambda-x)] f(\lambda) \psi(x)$

$$
=\int_{-\infty}^{+\infty} \mathrm{d} \lambda \delta(\lambda-x) f(\lambda) \psi(x)=f(x) \psi(x)
$$

## Mathematical Prerequisites II

## Probability Theory

Q Physics is concerned with describing the Nature
Q ...or, more accurately, our observations of Nature
Q Experiments are our questions posed to Nature,
Q...the experimental results are its (oft cryptic) answers

Q Theoretical physics endeavors to model Nature
Qby creating mathematical models that faithfully reproduce Nature
Q ...or, more accurately, its every answer to every conceivable question Every physical observation can be phrased in a binary form:
Q"The energy is 56.19 J " - T/F ( $=1 / 0$ )
Q"The energy is $56.19 \pm 0.50 \mathrm{~J}$ " - T/F $(=1 / 0)$
Q"The energy is between 56.00 and 57.00 J " - T/F ( $=1 / 0$ )
Q"(For $\mathrm{x}=0$ to 99) The energy is between x and $\mathrm{x}+1 \mathrm{~J}$ " - $\mathrm{T} / \mathrm{F}(=1 / 0)$ Qetc.

## Mathematical Prerequisites II

## Probability Theory

Q Experiments and experimental results are "events."
Q Notation: A, B, C = "events"
Q" $\neg$ A" is the logical opposite / complement (= "not A")
Q logical conjunction "A\&B" (= "A and B")
Qlogical disjunction "AvB" (= "A or $\mathrm{B} ") \quad$ vs. "AxB" (= "either A or $\mathrm{B} ")$
Q logical $\neq$ chronological
$Q$ Precedence: $\neg$ before $\&, v$, and $x$
" $\neg \mathrm{A} \& \mathrm{~B}$ " means " $(\neg \mathrm{A}) \& \mathrm{~B}$, " " $\neg \mathrm{AvB}$ " means " $(\neg \mathrm{A}) \mathrm{vB}$ "
Q Dependence: $\mathrm{AvB}=\neg((\neg \mathrm{A}) \&(\neg \mathrm{~B})), \mathrm{AxB}=(\mathrm{AvB}) \& \neg(\mathrm{~A} \& \mathrm{~B})$
QAlso, "A $=>\mathrm{B}^{\prime \prime}=(\neg \mathrm{A})_{\mathrm{vB}}$ implication ( $=$ "if A then B")
QBoth \& and v are:
Q idempotent [A\&A=A], associative $[A \&(B \& C)=(A \& B) \& C]$
Q commutative $\mathrm{A} \& \mathrm{~B}=\mathrm{B} \& \mathrm{~A}$, absorbing $\mathrm{A} \&(\mathrm{AvB})=\mathrm{A}=\mathrm{Av}(\mathrm{A} \& \mathrm{~B})$
QDistributive: $\mathrm{A} \&(\mathrm{BvC})=(\mathrm{A} \& B) \mathrm{v}(\mathrm{A} \& \mathrm{C})$ and $\mathrm{Av}(\mathrm{B} \& \mathrm{C})=(\mathrm{AvB}) \&(\mathrm{AvC})$

## Mathematical Prerequisites II

## Probability Theory

$Q \mathrm{P}(\mathrm{A} \mid \mathrm{B})=$ "The probability that A , provided/assuming B "
Q1. Reality: $0 \leq \mathrm{P}(\mathrm{A} \mid \mathrm{B}) \leq 1$
Q2. Certainty: $\mathrm{P}(\mathrm{A} \mid \mathrm{A})=1$
Q3a. Complementarity: $\mathrm{P}(\neg \mathrm{A} \mid \mathrm{B})=1-\mathrm{P}(\mathrm{A} \mid \mathrm{B}) \quad$ " $\mathrm{Av}(\neg \mathrm{A})$, no third option"
Q4. $\mathrm{P}(\mathrm{A} \& \mathrm{~B} \mid \mathrm{C})=\mathrm{P}(\mathrm{A} \mid \mathrm{C}) \cdot \mathrm{P}(\mathrm{B} \mid \mathrm{A} \& \mathrm{C})=\mathrm{P}(\mathrm{B} \mid \mathrm{C}) \cdot \mathrm{P}(\mathrm{A} \mid \mathrm{B} \& \mathrm{C})$ (Bayes' Thm.)
$Q^{2} \& 3: \mathrm{P}(\neg \mathrm{A} \mid \mathrm{A})=0$
Q Equivalently 3b. $\mathrm{P}(\mathrm{AvB} \mid \mathrm{C})=\mathrm{P}(\mathrm{A} \mid \mathrm{C})+\mathrm{P}(\mathrm{B} \mid \mathrm{C})-\mathrm{P}(\mathrm{A} \& \mathrm{~B} \mid \mathrm{C})$
Q Substitute $\mathrm{B}=\neg \mathrm{A}$, this reads $\mathrm{P}(1 \mid \mathrm{C})=\mathrm{P}(\mathrm{A} \mid \mathrm{C})+\mathrm{P}(\neg \mathrm{A} \mid \mathrm{C})-\mathrm{P}(0 \mid \mathrm{C})$ which reproduces Axiom 3 since $\mathrm{P}(1 \mid \mathrm{C})=1$ and $\mathrm{P}(0 \mid \mathrm{C})=0$
Bayes' Thm.: $\mathrm{P}(\mathrm{B} \mid \mathrm{A} \& \mathrm{C})=\mathrm{P}(\mathrm{B} \mid \mathrm{C}) \cdot \mathrm{P}(\mathrm{A} \mid \mathrm{B} \& \mathrm{C}) / \mathrm{P}(\mathrm{A} \mid \mathrm{C})$
Independence: If AiB then $\mathrm{P}(\mathrm{B} \mid \mathrm{A} \& \mathrm{C})=\mathrm{P}(\mathrm{B} \mid \mathrm{C})$
Q Then, Axiom 4: $\mathrm{P}(\mathrm{A} \& \mathrm{~B} \mid \mathrm{C})=\mathrm{P}(\mathrm{A} \mid \mathrm{C}) \cdot \mathrm{P}(\mathrm{B} \mid \mathrm{C})$
Q Probability as "limit frequency" or as "propensity"

## Mathematical Prerequisites II

 Probability TheoryQProbability distributions
QBinomial probability distribution
Q Individual experiments ( $E$ ) have two possible outcomes, $A$ or $\neg A$
$Q P(A \mid E)=p$ then $P(\neg A \mid E)=1-p$

$$
P\left(\#_{A} \mapsto k \mid E^{n}\right)=\binom{n}{k} p^{k}(1-p)^{n-k}
$$

Q Note:

$$
\begin{aligned}
\binom{n}{k} & :=\frac{n!}{k!(n-k)!}=\frac{n(n-1) \cdots(n-k+1)(n-k)!}{k!(n-k)!} \\
& =\frac{n}{1} \cdot \frac{n-1}{2} \cdots \frac{n-k+1}{k} \quad \begin{array}{c}
(p+q)^{n}=\sum_{k=0}^{n}\binom{n}{k} p^{k} q^{n-k} \\
\text { binomial formula }
\end{array}
\end{aligned}
$$

## Mathematical Prerequisites II

 Probability TheoryQ Average (=expectation value) of a probable quantity $A$

$$
\langle A\rangle:=\sum_{k=0}^{n} A_{k} P\left(A_{k} \mid E^{n}\right)
$$

QFor example, average $\#_{A}$

$$
\left\langle \#_{A}\right\rangle:=\sum_{k=0}^{n} k P\left(\#_{A} \mapsto k \mid E^{n}\right)
$$

For the binomial distribution

$$
\begin{aligned}
\left\langle \#_{A}\right\rangle & =\sum_{k=0}^{n} k\binom{n}{k} p^{k} q^{n-k}=\sum_{k=0}^{n}\binom{n}{k}\left(\frac{\partial p^{k}}{\partial p}\right) q^{n-k} \\
& =\frac{\partial}{\partial p} \sum_{k=0}^{n}\binom{n}{k} p^{k} q^{n-k}=\frac{\partial}{\partial p}(p+q)^{n}=n p
\end{aligned}
$$

Q So the frequency of $A$ becomes $\langle f(A ; n)\rangle=\frac{\left\langle \#_{A}\right\rangle}{n}=p$

## Mathematical Prerequisites II

 Probability TheoryQContinuous probability: $X$ has continuous values $x, g(x) \geq 0$
© Then (for $X \geq 0$ ):

$$
\begin{array}{rlrl}
\langle X\rangle & =\int_{0}^{\infty} g(x) \mathrm{d} x x \geqslant \int_{\epsilon}^{\infty} g(x) \mathrm{d} x x \geqslant \epsilon \int_{\epsilon}^{\infty} g(x) \mathrm{d} x x \\
& =\epsilon P(X \mapsto x \geqslant \epsilon \mid E) & P(X \mapsto x \geqslant \epsilon \mid E) \leqslant \frac{\langle X\rangle}{\epsilon}
\end{array}
$$

QThen, for $X \rightarrow|X-c|^{\alpha}$, for $\alpha>0$,

$$
P(|X-c| \geqslant \epsilon \mid E)=P\left(|X-c|^{\alpha} \geqslant \epsilon^{\alpha} \mid E\right) \leqslant \frac{\left.\langle | X-\left.c\right|^{\alpha}\right\rangle}{\epsilon^{\alpha}}
$$

is the Chebyshev inequality.
Since $\left.\langle | X-\left.c\right|^{2}\right\rangle=\sigma^{2}$ is the variance and $\langle X\rangle=c$ the mean, setting $\epsilon=k \sigma$,

$$
P(|X-\langle X\rangle| \geqslant k \sigma \mid E) \leqslant \frac{1}{k^{2}}
$$

The probability of $X$ being $k \sigma$-fold away from $c$ is $\leq 1 / k^{2}$.

## Mathematical Prerequisites II

 Probability TheoryQ Back to the binomial probability distribution
Similar results:

$$
P(A \mid E)=p \quad P\left(\left|\#_{A}-n p\right| \geqslant \epsilon \mid E^{n}\right) \leqslant \frac{\left\langle\left(\#_{A}-n p\right)^{2}\right\rangle}{\epsilon^{2}}
$$

$$
\left\langle\left(\#_{A}-n p\right)^{2}\right\rangle=\left\langle\sum_{i=1}^{n}\left(\delta_{E_{i} \mapsto A}-p\right)^{2}\right\rangle \leq n
$$

Q and for the relative frequency

$$
f(A ; n):=\frac{\#_{A}}{n} \quad P\left(|f(A ; n)-p| \geqslant \delta \mid E^{n}\right) \leqslant \frac{1}{n \delta^{2}}
$$

known as the law of large numbers.
It doesn't say that $f(A ; n)$ limits to $p$ or is close to $p$
Qbut that the deviations of $f(A ; n)$ from $p$ become increasingly improbable
Q probability of deviation of $f(A ; \eta)$ from $p$ becomes arbitrarily small

## Mathematical Prerequisites II

## Probability Theory

QInductive inference, prior and posterior probability
Q Estimate the propensity $p$ of the experiment $E$ to yield $A$.
$Q$ Repeating $E$ independently $n$ times, $A$ occurs $r$ times.
QBayes:

$$
\begin{aligned}
& P\left(p \mapsto \theta \pm \delta \mid\left(\#_{A} \mapsto r\right) \& E^{n}\right)=\frac{P\left(\#_{A} \mapsto r \mid(p \mapsto \theta \pm \delta) \& E^{n}\right) \cdot P\left(p \mapsto \theta \pm \delta \mid E^{n}\right)}{P} \frac{P\left(\#_{A} \mapsto E^{n}\right)}{\text { Q Binomial distribution: }}
\end{aligned}
$$

$$
P\left(p \mapsto \theta \pm \delta \mid\left(\#_{A} \mapsto r\right) \& E^{n}\right)=\left(\binom{n}{k} \theta^{r}(1-\theta)^{n-r}\right) \cdot P\left(p \mapsto \theta \pm \delta \mid E^{n}\right)
$$

posterior probability
prior probability
...still does not determine $p$.
If we (1) choose a uniform prior probability
Q ...and (2) maximize with respect to $\theta$, then:

$$
p=\max (\theta)=\frac{r}{n}
$$



